PREDICTING THE START WEEK OF RESPIRATORY SYNCYTIAL VIRUS OUTBREAKS USING REAL-TIME WEATHER VARIABLES

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

Respiratory Syncytial Virus (RSV), a major cause of bronchiolitis, has a large impact on the census of pediatric hospitals during outbreaks. Using readily available data, reliable prediction of the week these outbreaks will start could help pediatric hospitals better prepare for staffing and supplies.

Naïve Bayes (NB) classifier models were constructed using weather data from 1985 to 2008 considering only variables that were available in real time and that could be used to forecast the week in which an RSV outbreak would occur in Salt Lake County, Utah (SLC). Outbreak start dates were documented by a panel of experts using 32,509 records with ICD-9 coded RSV and bronchiolitis diagnoses from Intermountain Healthcare hospitals and clinics for the RSV seasons from 1985 to 2008.

NB models predicted RSV outbreaks up to three weeks in advance of the start date with an estimated sensitivity of up to 67% and estimated specificities as high as 94% to 100%. Temperature and wind speed were the best overall predictors, but other weather variables also showed relevance depending on how far in advance the predictions were made. The weather conditions predictive of an RSV outbreak in this study were similar to those that lead to temperature inversions in the Salt Lake Valley.

We demonstrate that Naïve Bayes classifier models based on weather data available in real time have the potential to be used as effective predictive models. These models may be able to predict the week that an RSV outbreak will occur with clinical relevance. Their clinical usefulness will be field tested during the next five years.

Dedicated to my beautiful daughter Chloe Lynne Walton—you were with us a short time, but we will always remember you.

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INTRODUCTION

Overcrowding is a problem that affects many tertiary care children's hospitals across the United States and has been associated with a number of problems affecting patients, staff, and hospital administrators. Both the Institute of Medicine and the American Academy of Pediatrics have described overcrowding as a major problem in pediatric hospitals across the nation [1, 2]. The problems associated with overcrowding have been addressed in the past through the use of appropriate management measures such as staffing and organizational changes [3, 4]. Forecasting hospital census may allow for timely implementation of management measures to alleviate some of the burden of overcrowding and lessen the associated problems [5]. There are many different patient conditions that drive patient census and creating a forecasting model that includes all of them would be a major undertaking. In this study we have decided to first examine one of the primary causes of hospital admissions during the time of year when pediatric hospitals experience the most overcrowding.

Pediatric hospitals in temperate climates have dramatic surges in patient census during the winter season. One of the primary causes of these surges are RSV outbreaks causing pediatric bronchiolitis [6-9]. Though RSV outbreaks typically occur in the winter in temperate climates, there is not a regular periodicity as to when they start, and the beginning of the outbreak usually falls somewhere within a three-month window [10, 11]. The driving factors behind RSV outbreaks are quite complex, and there is considerable evidence of an association between RSV outbreaks and weather conditions [12]. The availability of weather data and the ability to be forecasted with a reasonable degree of accuracy make the associated measures attractive candidates as potentially viable predictors for RSV outbreaks.

For this work we use Naïve Bayes (NB) classifiers as the method for constructing the prediction models because NB classifiers assess each variable independently and can easily handle missing values, which are common in the retrospective datasets used in this study. NB classifiers can also perform well with small training sets, such as the one used in this study due to the lack of long term epidemiology records, a situation that is exacerbated by the need to separate the data between low and high peak seasons. A NB classifier is a simple probabilistic classifier based on Bayes' theorem. NB classifiers are trained with a set of objects or instances with known class assignments; the features associated with each object are independently assessed to determine the probability of assignment to a particular class based on the value of each feature. Using these probabilities NB classifiers are then used to predict the class of objects with an unknown class assignment. The independence assumption of the NB classifier means that the presence or absence of a particular feature of a class is unrelated to the presence or absence of any other feature [13]. Despite their simple Naïve design and over-simplified assumptions, NB classifiers often perform as well as more sophisticated classifiers in real world complex problems studies [14-22].

BACKGROUND

Bronchiolitis is a major cause of hospital admissions during the winter and can cause severe hospital overcrowding. Respiratory syncytial virus (RSV) is a respiratory virus that can cause severe infection in infants and young children and is the leading cause of bronchiolitis in children under one year of age in the United States [10, 23-25]. RSV outbreaks cause a significant increase in hospital admissions during the winter season [24]. The ability to predict the start date of an RSV outbreak using readily available data may allow for the implementation of management strategies in a more timely, effective, and efficient fashion. Some possible improvements may include improved staff scheduling, improved rescheduling of elective procedures, anticipatory resource utilization and mobilization of respiratory supplies, improved timing of control measures, and improved timing for restricting visitation and grouping patients [26, 27].

RSV has a characteristic biennial outbreak pattern with alternating low peak and high peak seasons [24]. Mathematical models demonstrated that the pattern of high peak and low peak outbreaks can be explained by the variation in the number of susceptible individuals in the population, which is considerably diminished following a large outbreak [23, 25, 28]. The ‘high peak’ seasons tend to occur earlier in the year, have a higher peak, and a shorter duration. In contrast, the ‘low peak’ seasons occur later, have lower peaks, and a longer duration. [25] If, as suggested by the mathematical models, the different patterns observed for high and low seasons were due to the size of the susceptible population, one would expect that on a low outbreak season there would be a greater lag between outbreak stimulus and the exponential growth of confirmed RSV cases. The inference is that it takes the outbreak longer to infect a large number of individuals given the level of immunity already existing in the population due to large outbreaks during the previous year. Therefore, it is important to develop independent models for high peak and low peak years.

Although existent mathematical models describe RSV outbreaks, the prediction of outbreak start dates remains an unsolved problem [10, 23, 25, 28]. Current methods of identifying outbreak start date are all based on retrospective data. To our knowledge, there are no studies published in the biomedical literature that attempt to predict the start week of an RSV outbreak using variables that can be acquired in real time and that are appropriate for inclusion in a forecast model that can be used in a clinical setting. Among these variables, weather-related variables (such as temperature, humidity, and precipitation) have great potential to be predictive because many studies have correlated them with RSV outbreaks [12, 29-31]. To construct a predictive model for RSV outbreaks, one must consider the small training set resulting from the lack of long term epidemiology records and the need to separate the data between low and high peak seasons. Therefore, the objective of this investigation was to explore the feasibility of using weather variables with NB classifiers to predict RSV outbreaks and the concomitant increase in RSV-related admissions to a pediatric hospital.

METHODS

Weather Data

Weather data from 1985 to 2008 were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (http://cdo.ncdc.noaa.gov/CDO/cdo). Data from the Salt Lake International Airport weather station were used to represent weather for the entire Salt Lake County region.

RSV Diagnosis

Data representing the diagnosis of RSV were obtained from the Intermountain Healthcare Enterprise Data Warehouse (EDW). Records were selected for patients that reside in Salt Lake County, Utah, that met the following criteria: 1) laboratory confirmation of RSV by viral culture or direct fluorescent antibody (DFA) polymerase chain reaction (PCR); or 2) a discharge diagnosis coded with a bronchiolitis or RSV-related ICD-9 code, including: 466 acute bronchitis and bronchiolitis; 466.1 acute bronchiolitis; 466.11 acute bronchiolitis due to respiratory syncytial virus (RSV); and 466.19 acute bronchiolitis due to other infectious organism.

For the purpose of this study, an RSV season was defined as September 20th to July 15th of the following year. Diagnostic ICD-9 codes were used to select records from 1985 through 2008, providing data for 12 high- and 11 low-peak seasons. The laboratory criteria defined above was used to select records from 2002 through 2008. Viral testing laboratory data were not available prior to 2001; viral testing was routinely performed on patients seen at PCMC after 2003. Between August 24, 2004, and June 26, 2008, RSV-related laboratory results and ICD-9 codes for non-specific bronchiolitis were highly correlated (Kendall tau correlation statistic = 0.78), indicating that ICD-9 codes are a reasonable proxy for positive laboratory tests.

Determination of the Start Week of the Outbreak

Due to limitations of our data, it was first necessary to determine a reference standard for the start date of the outbreak to train and test our models. Currently, epidemiologists with the Center for Disease Control (CDC) use percent positive lab tests [32] and infectious disease specialists with Primary Children's Medical Center in Salt Lake City, Utah, use the number of laboratory confirmed cases in a seven-day window to determine the presence of an outbreak. Unfortunately, we were unable to use these criteria based on laboratory data to define the outbreaks because viral testing for RSV was not routinely available prior to 2001. In the absence of laboratory data, we used domain expert opinion in combination with available information from ICD9 codes to establish the reference standard for presence of outbreak [33-35]. Expert opinion was obtained by creating graphs of the number of patient records with ICD-9 codes for RSV and bronchiolitis over time for each season considered in this study (Figure 1). Each graph showed both the number of non-specific bronchiolitis ICD-9 coded cases for each day along with the number of RSV specific ICD-9 codes. RSV and bronchiolitis activity in the graphs was shown from mid September to mid June encompassing the entire RSV season for the seasons from 1985 to 2008. Ten infectious disease experts from the

Figure 1: Sample Page from Expert Panel Survey

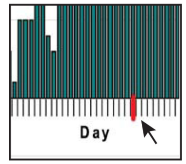
Name:______________________________________ Date:________________

Please indicate your best estimate of the following on the graph below
by making a mark in-between the vertical bars on the bottom of the
the graph:

1. The start of the outbreak
2. The peak of the outbreak
3. The end of the outbreak

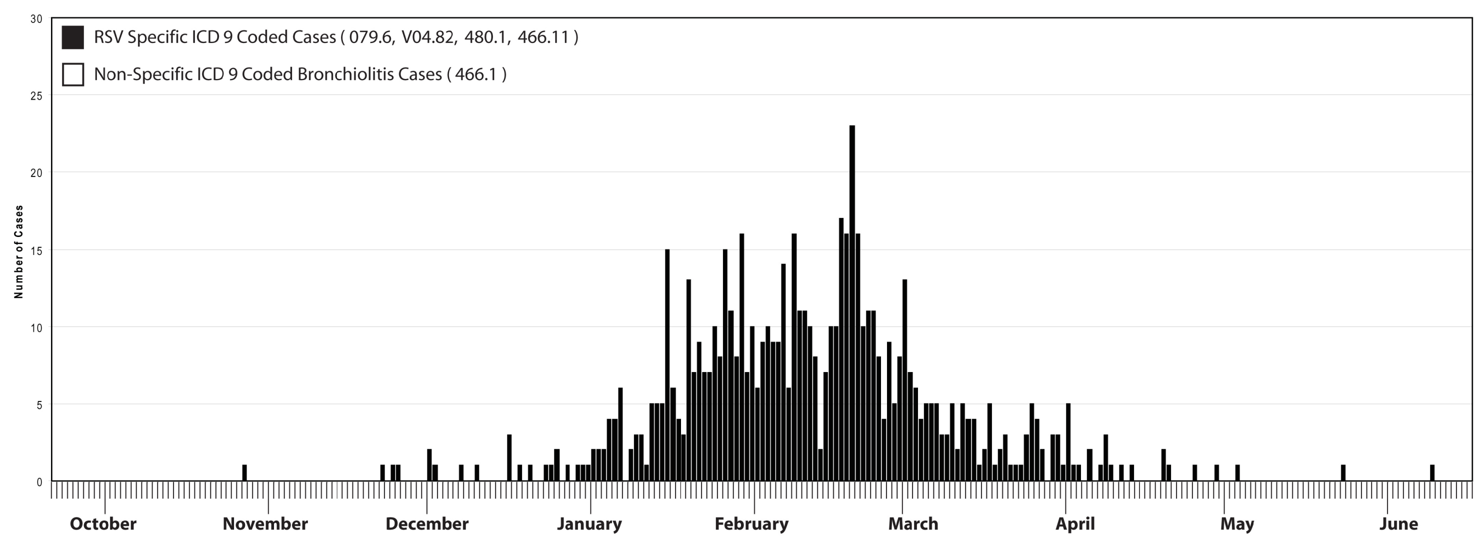
At the bottom of the page please mark on the scale your confidence level
for each estimate.

Example:



Please contact Nephi Walton with any questions:
nephi.walton@utah.edu
801-455-6227

Respiratory Syncytial Virus Cases In Salt Lake County for the 2001-2002 Season



Start Date Confidence Level

0 10 20 30 40 50 60 70 80 90 100%

Peak Date Confidence Level

0 10 20 30 40 50 60 70 80 90 100%

End Date Confidence Level

0 10 20 30 40 50 60 70 80 90 100%

University Of Utah Department Of Pediatrics were asked to independently assess the date at which the outbreak started for each season. The outbreak start week was then chosen based on the Sunday of the week a majority of the physicians identified as the outbreak starting date.

Naïve Bayes Classifier

We analyzed several data mining methods to solve this complex problem. Although there is a large amount of data to be mined, the actual historical time points of prediction in this problem are very few because there is only one outbreak that occurs each year. This problem is approached as a classification problem where a given week is classified as outbreak or no outbreak given a large set of historical data on which to base the classification. Using time series analysis type predictions and forecasting models will not work for this problem because once the outbreak occurs the predictor variables are no longer relevant. Our dataset consists of a large number of weather inputs with a small number of historical outcomes to which they are compared. We initially tried a neural network approach to solving this problem, but the data partitioning requirements for neural networks created a training data set that was too small to be effective. NB classifiers where chosen for this project because they require only two data partitions (one for training and another for validation) which allowed for increased size of our test set and achieved better results [37]. One of the advantages of neural networks over the basic NB classifier is the ability to take into account any interaction effects that take place between variables. Despite the simplicity of NB classifiers they have surprisingly good performance and have had comparable performance to neural networks in many similar studies [14-22].

For each variable used to classify a week as an outbreak or no outbreak, we create a probability that an outbreak will occur based on the value of that variable in history during the weeks that outbreaks occurred. This probability is called the posterior probability. Naïve Bayes classifiers use a set of posterior probabilities to determine a probability that an unknown will fall into a certain class; so in a sense the NB classifier is creating a model that develops a probability of a classification based on inductive learning. Using maximum temperature as an example, we know that RSV outbreaks in SLC only begin in the fall or the winter. Based on past observations the temperature at the beginning of an outbreak in SLC has never been higher than 90 degrees. So if the temperature used for classification is 100 degrees, the probability of an outbreak based on past experience is zero and the probability of not being the start week of an outbreak is 100%. However since NB classifiers assess each variable independently, having another variable such as wind speed could increase the overall probability of an outbreak regardless of the value of temperature. The NB classifier uses the probabilities for each variable independently and then compares the overall probability of an outbreak with the overall probability of not having an outbreak, and then classifies the week as outbreak or no outbreak according to whichever has the highest overall probability. This model can be updated as more experience is gained to increase the accuracy.

The weather dataset was obtained from the NOAA website. Text files consisting of comma separated values were downloaded for the years 1985 through 2008. A visual basic function was then written to import the text file and appropriately format the values into a Microsoft Access database table. The table consisted of four fields: “value,” “measure,” “date,” “station.” Where measure was the variable being studied, value is the measured value of the variable on a given date, and date was the date the measurement took place. Station contained the weather station where the value was measured. Values from multiple stations were downloaded, but only measurements from the Salt Lake International Airport were used in this study. Using this table format it is easy to add additional variables to our study without changing the table structure. Once the data was imported it was assessed within the database for missing values and outliers. During this process it was discovered that variables associated with UV light had insufficient data for the model, having values recorded for less than half of the time period of the retrospective study. For this reason UV light related variables were not used in this study. All other variables included in the study were free from error in our assessment and did not have missing values.

Once the data were imported and cleaned, the next step was to generate output files from the database that could be used as inputs to Statistica Data Miner for constructing NB models. A Visual Basic application was constructed within the database application to create a grid of variable values with related prediction end points of “outbreak” or “no outbreak,” as shown in Figure 2.

Inputs								Output
O-8	O-7	O-6	O-5	O-4	O-3	O-2	O-1	Outbreak Week (O)
					Inputs wk 3	Inputs wk 2	Inputs wk 1	Y
				Inputs wk 3	Inputs wk 2	Inputs wk 1		N
			Inputs wk 3	Inputs wk 2	Inputs wk 1			N
		Inputs wk 3	Inputs wk 2	Inputs wk 1				N
	Inputs wk 3	Inputs wk 2	Inputs wk 1					N
Inputs wk 3	Inputs wk 2	Inputs wk 1						N

Figure 2: Visual Representation of NB Classifier Input Data Structure

The constructed application requires input of a set of outbreak dates, the number of nonoutbreak weeks to include for each outbreak week, the number of days of data as inputs for each prediction, and the variables to be included in the output. For this study we used 21 days of prediction variable values and included all the weather variables; six non-outbreak weeks preceding the outbreak week were included. Separate files were generated for low peak and high peak outbreak seasons. This process generated a large Excel spreadsheet similar to what is shown in Figure 2 that could be opened in Statistica Data Miner for analysis. In addition to formatting the data, additional columns were added to denote whether each prediction set was part of the training set or testing set. These divisions are shown in Figure 3.

This large spreadsheet was then imported into Statistica Data Miner to perform the data mining analysis. To facilitate testing every possible combination of variables, a Visual Basic script was written within Statistica Data Miner to automate this process. All the variables were input as continuous variables with normal distributions. No weighting was applied to any of the variables as there was no evidence thus far to assume that any variable had more influence on the outcome than another. The output was set as a categorical variable containing two possible values, 1 and 0. 1 denotes an outbreak week and 0 denotes a nonoutbreak week. The data were divided into test and training sets as described above and all results were compiled in a large spreadsheet. Results were output for testing and training sets, but only testing set results were used as the results in this study.

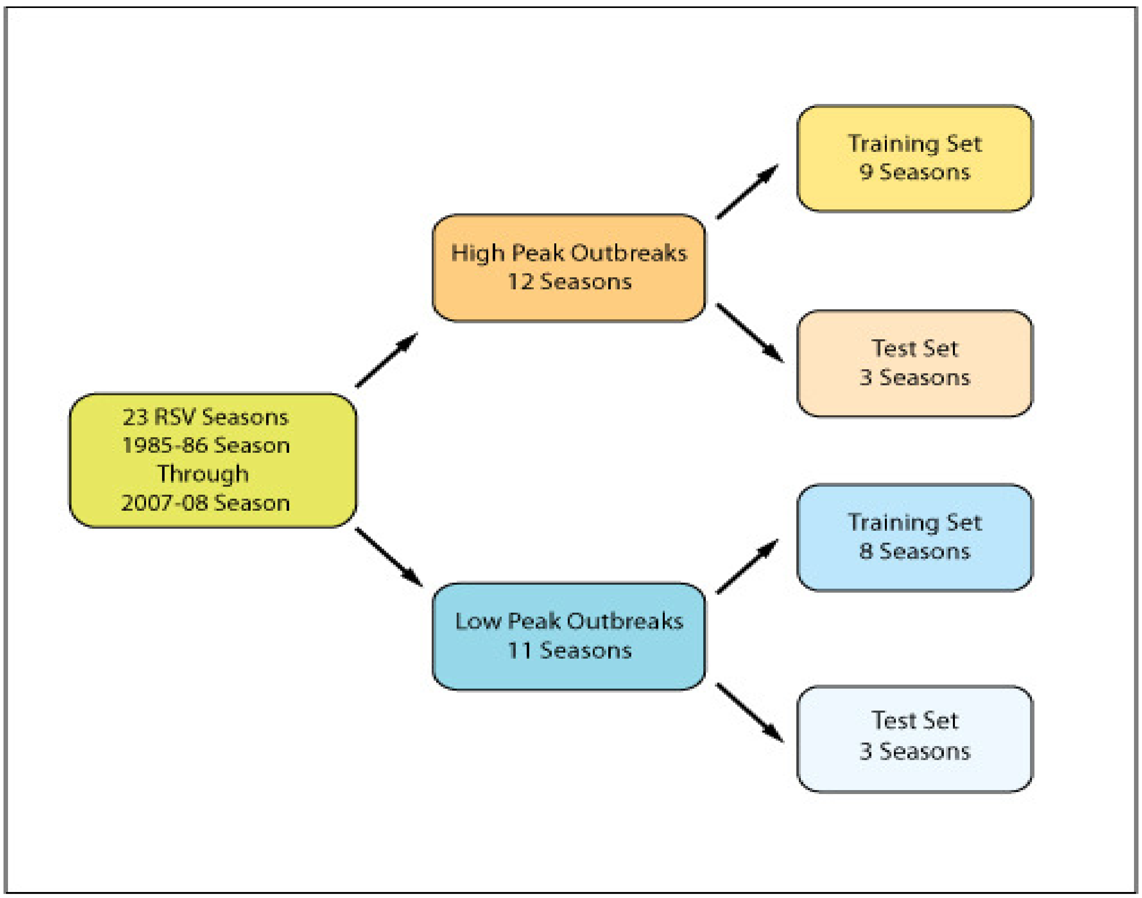


Figure 3: Schema of Data Segregation

Among the 23 seasons available for analysis, there were 12 high- and 11-low peak outbreak seasons (Figure 3). The early seasons were used for training the models and the three latest seasons were used for testing the high- and low-peak models (Figure 3). We induced Naïve Bayes models for every possible combination of the eight selected variables; thus, we induced a total of 255 unique NB classifiers. Each of the models has a unique set of predictor weather variables, X = {x1,x2,x...,xd}. For each predictor variable a posterior probability is calculated for the event C_j with the possible outcomes C = 1 (outbreak occurs) and C = 0 (no outbreak occurs) using Bayes' rule: $p(C_j \mid x_1,x_2,\ldots,x_d) \propto p(x_1,x_2,\ldots,x_d|C_j)\, p(C_j)$ where $p(C_j \mid x_1,x_2,x\ldots,x_d)$ is the posterior probability of class membership or the probability that X belongs to C_j. These posterior probabilities are calculated using all of the available historical weather and outbreak data where the outbreak classification C_j is known. Since NB assumes that the conditional probabilities of the independent variables are statistically independent the likelihood can be expressed as a product of terms:

$$p(X \mid C_j) \propto \prod_{k=1}^{d} p(x_k \mid C_j)$$

and the posterior can then be rewritten as:

$$p(C_j \mid X) \propto p(C_j) \prod_{k=1}^{d} p(x_k \mid C_j)$$

The NB classifier uses Bayes' rule above to assign a given week X for which the outbreak status is unknown, to outbreak classification C_j that achieves the highest posterior probability. The exhaustive building and comparison of all possible models was motivated by unsuccessful attempts to use variable selection algorithms with our current data. The NB classifier models were generated using Statistica Data Miner version 9 (Stat Soft, Inc., Tulsa, OK, USA).

The NB classifier was trained with a series of values for daily weather variables and a flag indicating whether, according to the determination of the expert panel, an outbreak occurred in the week following the last Sunday in the data set. As shown in Figure 2, models were run with three weeks of data as input (i.e., for each 3 week period each weather variable has 21 values, one value for every day of each week). Separate classifiers were built for predicting the outbreak in the same week, one week in advance of the outbreak, two weeks in advance of the outbreak, and three weeks in advance of the outbreak, respectively. To predict the outbreak in advance, a sliding window was used. The output remained the same but the input window would slide back one week, overlapping the data used in the previous prediction by two weeks. This process was repeated again as the prediction week was moved forward by sliding the window back one week each time (see Figure 2). In the training sets for each week in which an outbreak occurred, there were six weeks of data included prior to when the outbreak occurred. These weeks were set to a negative flag value when no outbreak occurred. For the high peak years, there were nine ‘outbreak’ weeks and 54 ‘no outbreak’ weeks in the training set and three ‘outbreak’ weeks and 18 ‘no outbreak’ weeks in the test set. Similarly, for the low peak years, there were eight ‘outbreak’ weeks and 48 ’no outbreak’ weeks in the training set, and three ‘outbreak’ weeks and 18 ‘no outbreak’ weeks in the test set. Unique NB classifiers were induced for every possible combination of variables in both high- and low-peak seasons for 0, 1, 2, and 3 weeks in advance of the outbreak, generating a total of 2040 NB models. The comprehensive list of the weather variables used in each of the models considered, along with the sensitivity and specificity in both training and test sets for both high-peak and low-peak seasons, are presented in the supplementary material.

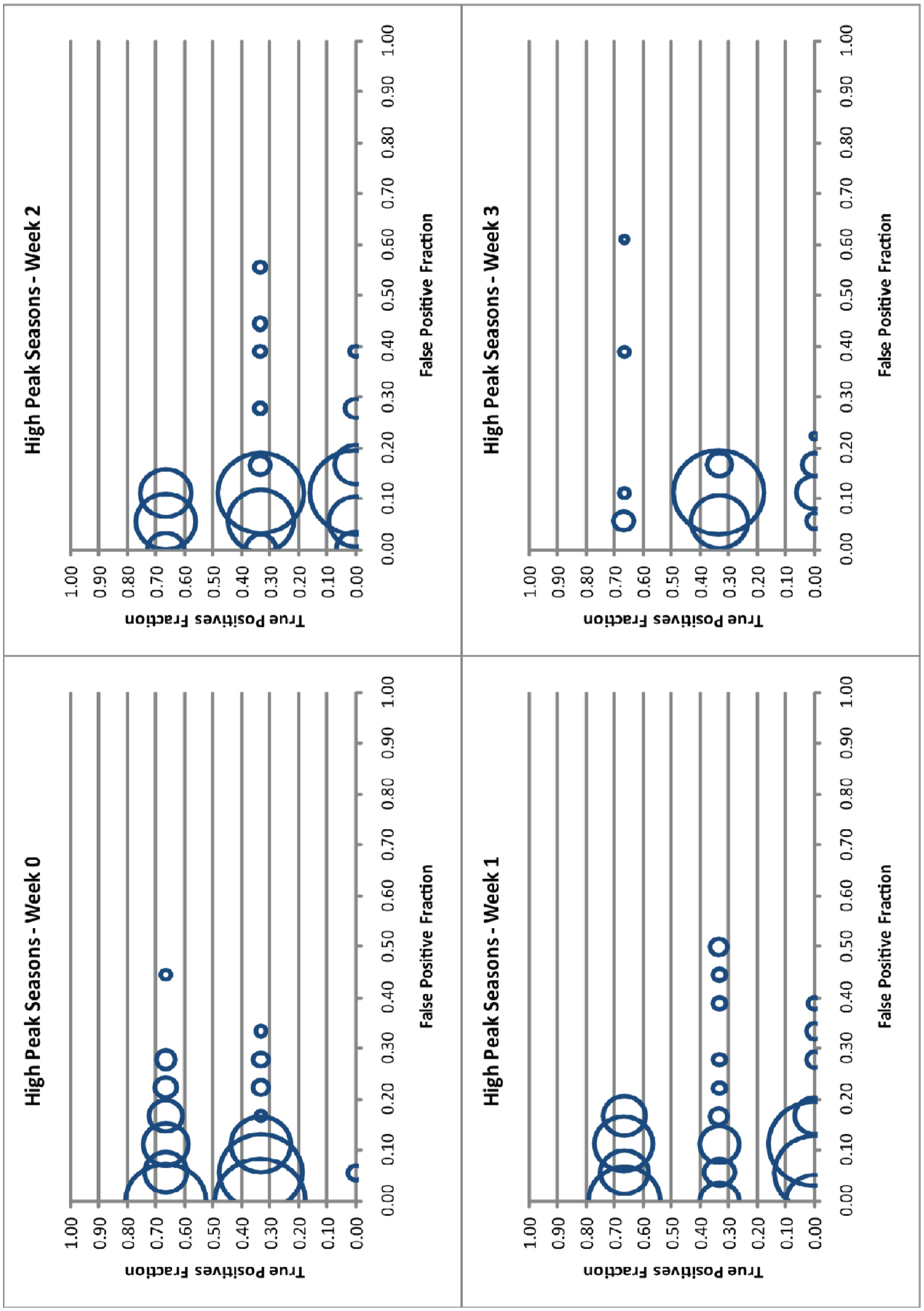
Institutional Review Board approval to perform this study was obtained from Intermountain Healthcare and the University of Utah.

RESULTS

Model Performance

For the high peak seasons, the NB classifier models predicting the outbreak in the same week achieved a sensitivity of 67% with specificities of up to 100% on the test set. This accuracy was achieved by 51 of the 255 different models that can be constructed using all the possible combinations of the weather variables tested in this study. It is important to note however that the reduced test set of three years means that sensitivity and specificity can only have the values of 0, 1/3, 2/3 and 1. The best models predicting the outbreak one week in advance achieved the same accuracy as those predicting the outbreak in the same week, but only 35 of the 255 variable combinations achieved this level of performance. Only nine models predicting the outbreak two weeks in advance achieved the same accuracy. Finally, the seven best models predicting the outbreak three weeks in advance reached the same sensitivity, 67%, but had a lower maximum specificity of 94%. Figure 4 depicts the true positive fraction and false positive fraction for the test set for all possible NB models using the 255 combinations of weather variables to predict high peak outbreaks in the week of the outbreak (Week 0), one week in advance (Week 1), two weeks in advance (Week 2) and three weeks in advance (Week 3).

Figure 4: Graph of NB Classifier Models—High Peak Seasons. The true positive fraction (y-axis) is graphed against false positive fraction (x-axis) for NB classifier models for high peak seasons and for every possible variable combination (n=255) of the weather variables used in this study. The size of each circle represents the number of NB classifier models that obtained the given accuracy. Each model predicts an RSV outbreak the Sunday preceding the outbreak (Week 0), one week in advance (Week 1), two weeks in advance (Week 2), and three weeks in advance (Week 3).

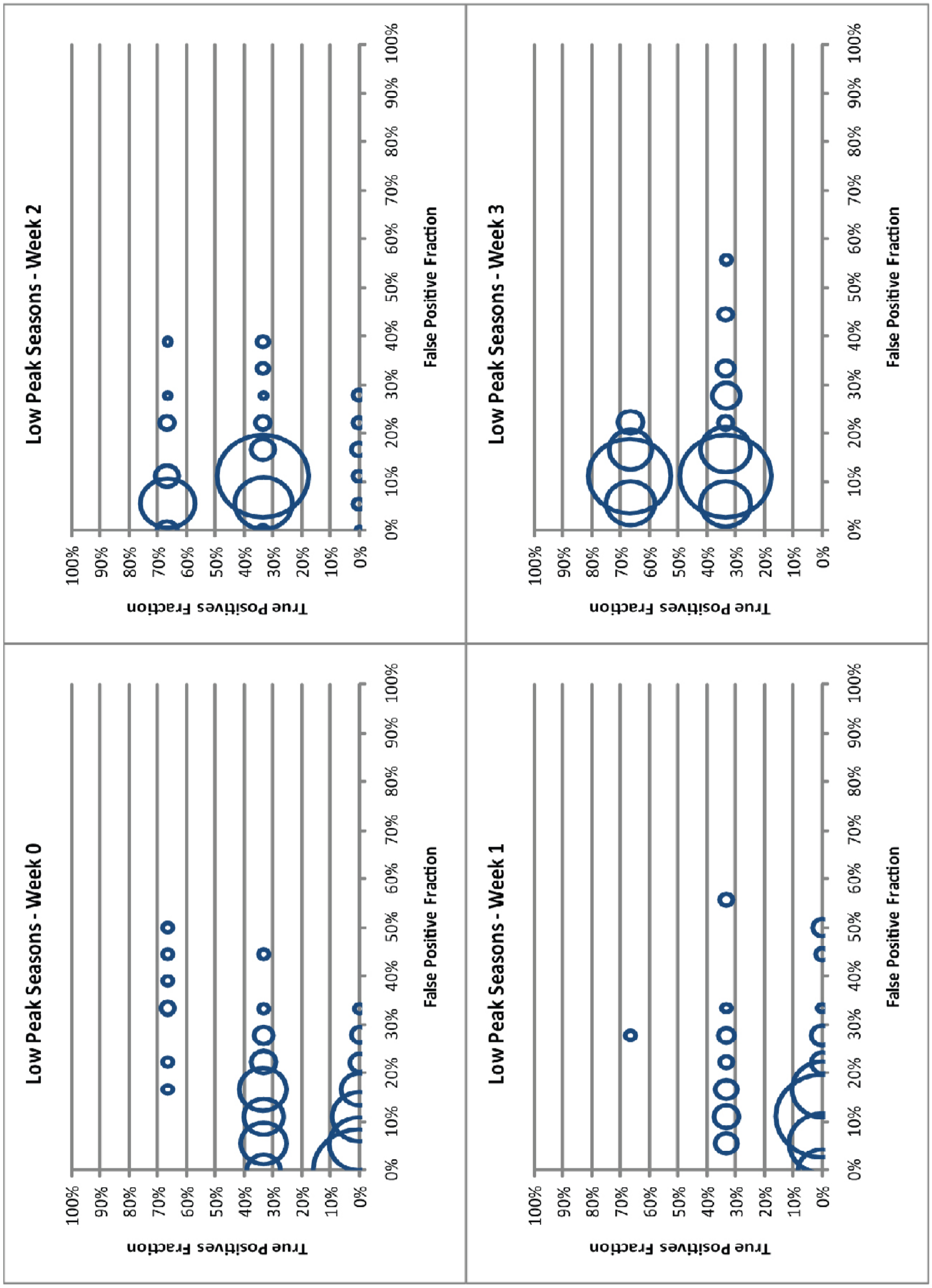

High Peak Seasons - Week 0
High Peak Seasons - Week 1
High Peak Seasons - Week 2
High Peak Seasons - Week 3
True Positives Fraction
False Positive Fraction
0.00 0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80 0.90 1.00

For the low-peak seasons, the NB classifier models predicting the outbreak in the same week achieved a sensitivity of 67% with a specificity of up to 83%. This accuracy was achieved by only one of the 255 possible models, with most of the other models (see Figure 5) achieving results no better than chance (100% combined sensitivity and specificity on the test set). Models predicting the outbreak one week in advance produced similar results, with only one achieving the same sensitivity but with a decreased specificity of 72%. Most other models also performed at or below chance (see Figure 5). Overall predictive accuracy increased significantly for models attempting to predict the outbreak two or three weeks in advance. The six best models predicting the outbreak two weeks in advance achieved a sensitivity of 67% with a specificity of 100% and the 32 best models predicting the outbreak three weeks in advance achieved a sensitivity of 67% and a specificity of 94%.

Figure 5 depicts the true positive fraction and false positive fraction for the test set for all possible NB models using the 255 combinations of weather variables to predict low peak outbreaks in the week of the outbreak (Week 0), one week in advance (Week 1), two weeks in advance (Week 2) and three weeks in advance (Week 3).

As discussed above, in most cases there was no single model that can be clearly considered the best for predicting the start of an outbreak one, two, or three weeks in advance. Inspection of the tables in the supplementary material and Figures 4 and 5 shows that numerous models can be considered equally appropriate, depending on the selection criteria (i.e., sensitivity, specificity, different combinations of them, performance on the test set or the training set, etc.) Given the

Figure 5: Graph of NB Classifier Models—Low Peak Seasons. The true positive fraction (y-axis) is graphed against false positive fraction (x-axis) for NB classifier models for low peak seasons and for every possible variable combination (n=255) of the weather variables used in this study. The size of each circle represents the number of NB classifier models that obtained the given accuracy. Each model predicts an RSV outbreak the Sunday preceding the outbreak (Week 0), one week in advance (Week 1), two weeks in advance (Week 2), and three weeks in advance (Week 3).


Low Peak Seasons - Week 0
Low Peak Seasons - Week 1
Low Peak Seasons - Week 2
Low Peak Seasons - Week 3
True Positives Fraction
False Positive Fraction
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

limited number of outbreaks in our testing data, this finding is not surprising. A larger set of testing data is necessary to adequately describe performance.

Individual Variable Performance

The relative importance of a single weather variable contributing to the best performing models was defined as the percentage of times a variable was included in the best performing models for each type of prediction (Table 1). Best performing models were defined as those with a sensitivity of at least 67% and a specificity of at least 94%. For high-peak seasons, wind speed is the variable most consistently encountered in the best models making predictions for the week of the outbreak and one and two weeks in advance, but it is less represented in the best models for predicting three weeks in advance of the outbreak. The three temperature variables (minimum, average and maximum) are similarly represented in the best models that predict for the week of the outbreak and one week in advance, however minimum temperature is more frequently included in the models that best predict the outbreak two and three weeks in advance. As shown in Table 1, three variables (atmospheric pressure, maximum relative humidity, and minimum relative humidity) were found in the best models that predict for the week of the outbreak and one week in advance but were less likely to be found in models that predict outbreaks two and three weeks in advance. Precipitation was not present in any of the top performing models for high-peak outbreak seasons.

For low-peak seasons, the analysis of the weather variables included only the models that can reasonably predict an outbreak. The predictions for the week of the outbreak and one week in advance of the outbreak are probably not significant since these models have only one variable combination that achieves the top performance and they both perform much worse than any other model considered here. For top performing models in low-peak seasons, wind speed appears in over 50% of the best models for predictions two weeks in advance and then drops to less than 20% for predictions three weeks in advance. The minimum temperature appears in almost 60% of the predictive models for predictions two weeks and three weeks in advance. Similar to high-peak seasons, precipitation was not present in any of the top performing models for low-peak seasons. Atmospheric pressure appears in 51% of the models predicting 2 weeks in advance and drops to 22% of the models predicting the outbreak three weeks in advance. Maximum relative humidity appears in 51% of models predicting two weeks in advance while minimum relative humidity only appears in 2% of models two weeks out; both have identical representation in predictions three weeks out, appearing only in 22% of the top performing models.

Table 1

Highest Performance Models

	Average Daily Pressure	Average Daily Wind Speed	Minimum Humidity	Maximum Humidity	Daily Precipitation	Minimum Temperature	Maximum Temperature	Average Daily Temperature
Week 0	47%	94%	57%	51%	0%	55%	63%	55%
Week 1	44%	86%	58%	46%	0%	54%	64%	64%
Week 2	24%	47%	29%	74%	0%	71%	68%	71%
Week 3	14%	29%	0%	0%	0%	100%	57%	71%

Percentage of models that include each variable in the highest performance models, based on achieving a minimum sensitivity of 67% and minimum specificity of 94%, for each advanced prediction for high peak seasons.

DISCUSSION

Overall, the input variable temperature, expressed as maximum, average or minimum, consistently appears in the best predictive models, with one of the three temperature variables appearing in over 90% of the best performing models for any prediction attempted. The importance of temperature as a predictive variable increases the further in advance the predictions are made from the start of an outbreak. The atmospheric pressure appears to be an important factor for predicting the outbreak in the week of the outbreak and one week in advance, but less important in predictions models two and three weeks in advance of an outbreak. These results suggest that the variables most commonly encountered in the best models for predicting RSV outbreaks are similar to those associated with the development of temperature inversions in the Salt Lake Valley [38]. Interestingly, inversions are always associated with a severe increase in levels of air pollutants that have been consistently correlated with respiratory health issues [39-41].

To further our investigation, we attempted to use air pollution indicators as predictive factors for RSV outbreaks. Several attempts were performed to develop NB models using air pollution variables (e.g., PM 10, and concentration of CO and SO_2) without success. Unfortunately, the data available for concentrations of PM 2.5, an air pollution indicator that has shown some association with bronchiolitis [42-44], is not sufficient to appropriately train a NB classifier. Analysis of only nine years of PM 2.5

data suggested that the concentration of these particles may have predictive value to forecast RSV outbreaks, but definite answers must wait until sufficient years of retrospective PM 2.5 data become available.

According to our literature review, wind speed has not been reported as a good predictor for RSV outbreaks. In contrast, wind speed was predictive in our analysis. The unique geography of the Salt Lake Valley contributing to the common occurrence of inversions in winter may account for this discrepancy as wind (or lack thereof) plays a vital role in the creation of inversions.

The difference in findings for high- and low-peak outbreak years agree well with what it is expected if RSV outbreak biannual patterns are a result of changes in the susceptible population. In low-peak years, the number of susceptible individuals is lower than in high-peak years; therefore, it is expected that even if the meteorological conditions exist to start an outbreak, the time for the outbreak to spread will be longer due to herd immunity. The speed of transmission is slower when more of the population exhibits immunity. This observation agrees very well with our relative lack of success in predicting outbreaks during the week the outbreak occurred and one week in advance during low-peak seasons. In contrast, during high-peak years, the number of cases quickly ramp up once the appropriate meteorological conditions exist to start the outbreak, leading to good predictive power for these short-term predictions.

Our study has limitations. Data limitations allowed for only rough performance estimates for unique models. Because of the limited number of seasons on which this model was tested, it is possible that large changes in sensitivity and specificity could be a reflection of limited data rather than actual model performance. The question of which model to implement in practical applications remains unanswered, and will depend upon refined performance estimates as data availability increases or the desire to select models with increased sensitivity or specificity to meet the operational needs of the hospital. Despite these limitations, the results validate our decision to use different models for high- and low-peak seasons and are consistent with the existing models to explain high- and low-peak seasons based on the size of the susceptible population. To address the limitations we identified, we will evaluate prediction models prospectively in the Salt Lake County region for the next five years.

Use of the results presented here in other geographic locations would require NB training with local weather data to account for the changing characteristics of RSV outbreaks in different regions with different climates and varying geographic features. However, it is likely that the same climate variables and methods could be used to build a predictive model in other locations, particularly if they have similar climates and geography to the Salt Lake County area.

The basic NB classifier assumes that all predictor variables are independent; by using this method we are assuming that there is no interaction between weather variables that may drive RSV outbreaks. However, in this case and in most real life processes there are complex interactions between predictor weather variables and they are not truly independent. There are ways to model some of these interactions or ease the independence assumptions with extensions to NB models. Laplacian correction is a method of shrinking the probability estimates to ease the independence assumption. It is also possible to introduce conditional probabilities in the model to account for interactions between variables [45]. Another method of modeling interactions is to combine NB models with tree methods splitting the overall dataset into subpopulations based on the values of the some of the predictor variables [46]. With an improved understanding of how weather is associated with RSV outbreaks, some of these more complicated methods may allow for better predictions.

CONCLUSION

Weather-related measurements available in real time have the potential to predict RSV outbreaks. These results are consistent with previous studies that indicate low-peak and high-peak outbreak seasons have different population dynamics, which most likely would lead to a lag between stimulus and event for low-peak outbreak seasons. In this study, it appears that weather conditions leading to outbreaks may be conditions that also lead to the establishment of a temperature inversion in the Salt Lake Valley, which in turn creates a condition of more polluted air known to impact respiratory health.

Significance to Biomedical Informatics

This work demonstrates how to integrate several informatics techniques, data retrieval, data analysis and classification techniques to solve a very important practical problem in medical practice: predicting when an RSV outbreak can occur since an outbreak usually affects a pediatric facility. The work includes a comprehensive analysis of the important biomedical informatics problem of forecasting infectious disease outbreaks to potentially allow for improved hospital management. This work is the first that we know of that makes an attempt to predict RSV outbreak start dates, a problem that has been acknowledged in the literature. We were able to demonstrate we could retrospectively determine start dates of outbreaks by extracting data from the electronic data warehouse and presenting it in a way that could be subjected to human analysis. We were also able to analyze and validate the use of real time variables that can be used in prediction models for this problem and for other informatics questions. Using well established data mining techniques we were able to construct models that can be used to solve important biomedical informatics problems.

This work represents a significant step in building disease outbreak forecasting systems. Providing a foundation for the determination of start dates from retrospective models and presenting a novel but basic data mining model to outbreak prediction that can be applied to many other disease outbreaks. Though the variables and outbreak patterns of other infectious diseases may be different, the basic prediction model and methods of analysis here should apply well to many other diseases in both similar and very different geographical regions.

Future Directions

In the future, NB prediction models should be built that include pollution measurements as inputs. The models included in this study, as well as more complex models that include pollution measurement should be tested prospectively in a clinical setting.

APPENDIX

The following tables contain a comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for both high peak and low peak seasons are presented in the supplementary material.

Table 2

Weather Variables Used for Predicting Outbreak During Week—
High Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak during the week of the outbreak for high peak years.

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
67%	96%	33%	94%	X							
89%	96%	0%	94%	X	X						
89%	94%	33%	100%	X	X	X					
78%	83%	67%	100%	X	X	X	X				
78%	83%	67%	100%	X	X	X	X	X			
89%	91%	33%	94%	X	X	X	X	X	X	X	
89%	83%	33%	100%	X	X	X	X	X	X	X	
89%	83%	33%	100%	X	X	X	X	X	X	X	X
89%	87%	33%	100%	X	X	X	X	X	X	X	X
78%	81%	67%	100%	X	X	X	X	X		X	
78%	78%	67%	100%	X	X	X	X	X		X	X
78%	81%	67%	100%	X	X	X	X	X			X
89%	87%	33%	100%	X	X	X	X		X		
89%	83%	33%	100%	X	X	X	X		X	X	
89%	80%	33%	100%	X	X	X	X		X	X	X
89%	87%	33%	100%	X	X	X	X		X		X
78%	78%	67%	100%	X	X	X	X			X	
78%	78%	67%	100%	X	X	X	X			X	X
78%	83%	67%	100%	X	X	X	X				X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	89%	33%	100%	X	X	X		X			
89%	91%	33%	89%	X	X	X		X	X	X	
89%	89%	33%	94%	X	X	X		X	X	X	
89%	85%	33%	100%	X	X	X		X	X	X	X
89%	91%	33%	100%	X	X	X		X	X	X	X
78%	83%	67%	100%	X	X	X		X		X	
78%	81%	67%	100%	X	X	X		X		X	X
78%	87%	33%	100%	X	X	X		X			X
89%	94%	33%	89%	X	X	X			X		
89%	87%	33%	94%	X	X	X			X	X	
89%	85%	33%	100%	X	X	X			X	X	X
89%	89%	33%	100%	X	X	X			X		X
78%	83%	67%	100%	X	X	X				X	
78%	80%	67%	100%	X	X	X				X	X
78%	89%	33%	100%	X	X	X					X
89%	89%	33%	100%	X	X		X				
78%	89%	67%	100%	X	X		X	X			
89%	89%	33%	100%	X	X		X	X	X	X	
89%	87%	33%	100%	X	X		X	X	X	X	
89%	85%	33%	100%	X	X		X	X	X	X	X
89%	89%	33%	100%	X	X		X	X	X	X	X
78%	81%	67%	100%	X	X		X	X		X	
78%	78%	67%	100%	X	X		X	X		X	X
78%	83%	67%	100%	X	X		X	X			X
89%	87%	33%	100%	X	X		X		X		
89%	85%	33%	100%	X	X		X		X	X	
89%	85%	33%	100%	X	X		X		X	X	X
89%	85%	33%	100%	X	X		X		X		X
78%	80%	67%	100%	X	X		X			X	
78%	80%	67%	100%	X	X		X			X	X
78%	85%	33%	100%	X	X		X				X
89%	94%	33%	94%	X	X			X			
100%	85%	33%	78%	X	X			X	X	X	
89%	89%	33%	100%	X	X			X	X	X	
89%	87%	33%	100%	X	X			X	X	X	X
89%	89%	33%	100%	X	X			X	X	X	X
78%	85%	67%	100%	X	X			X		X	
78%	83%	67%	100%	X	X			X		X	X
78%	89%	33%	100%	X	X			X			X
100%	74%	67%	72%	X	X				X		
89%	85%	33%	100%	X	X				X	X	
89%	85%	33%	100%	X	X				X	X	X
89%	85%	33%	100%	X	X				X		X
89%	87%	67%	100%	X	X					X	

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	85%	67%	100%	X	X					X	X
89%	91%	33%	100%	X	X						X
78%	83%	33%	100%	X		X					
78%	76%	33%	100%	X		X	X				
78%	70%	67%	94%	X		X	X	X			
89%	81%	33%	89%	X		X	X	X	X	X	
89%	80%	33%	94%	X		X	X	X	X	X	
89%	81%	33%	94%	X		X	X	X	X	X	X
89%	83%	33%	94%	X		X	X	X	X	X	X
78%	69%	67%	94%	X		X	X	X		X	
78%	67%	67%	89%	X		X	X	X		X	X
78%	72%	33%	100%	X		X	X	X			X
89%	81%	33%	89%	X		X	X		X		
89%	80%	33%	94%	X		X	X		X	X	
89%	80%	33%	94%	X		X	X		X	X	X
89%	81%	33%	94%	X		X	X		X		X
78%	70%	67%	89%	X		X	X			X	
78%	67%	67%	89%	X		X	X			X	X
78%	74%	33%	100%	X		X	X				X
78%	78%	33%	89%	X		X		X			
89%	83%	33%	89%	X		X		X	X	X	
89%	81%	33%	89%	X		X		X	X	X	
89%	81%	33%	94%	X		X		X	X	X	X
89%	81%	33%	94%	X		X		X	X	X	X
78%	70%	67%	89%	X		X		X		X	
78%	69%	67%	94%	X		X		X		X	X
78%	78%	33%	100%	X		X		X			X
89%	83%	67%	89%	X		X			X		
89%	85%	33%	89%	X		X			X	X	
89%	80%	33%	94%	X		X			X	X	X
89%	85%	33%	94%	X		X			X		X
78%	72%	67%	100%	X		X				X	
78%	70%	67%	100%	X		X				X	X
78%	78%	33%	100%	X		X					X
78%	76%	33%	100%	X			X				
78%	74%	33%	100%	X			X	X			
89%	81%	33%	94%	X			X	X	X	X	
89%	78%	33%	94%	X			X	X	X	X	
89%	78%	33%	94%	X			X	X	X	X	X
89%	81%	33%	94%	X			X	X	X	X	X
78%	67%	67%	89%	X			X	X		X	
78%	69%	67%	89%	X			X	X		X	X
78%	70%	33%	100%	X			X	X			X
89%	78%	67%	94%	X			X		X		

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	78%	33%	94%	X			X		X	X	
89%	78%	33%	94%	X			X		X	X	X
89%	81%	33%	94%	X			X		X		X
78%	69%	67%	94%	X			X			X	
78%	69%	67%	94%	X			X			X	X
78%	76%	33%	100%	X			X				X
78%	91%	33%	94%	X				X			
100%	78%	33%	72%	X				X	X	X	
89%	81%	33%	89%	X				X	X	X	
89%	80%	33%	94%	X				X	X	X	X
89%	81%	33%	94%	X				X	X	X	X
78%	70%	33%	100%	X				X		X	
78%	72%	33%	100%	X				X		X	X
78%	80%	33%	100%	X				X			X
100%	59%	33%	67%	X					X		
89%	78%	67%	89%	X					X	X	
89%	81%	33%	94%	X					X	X	X
89%	81%	0%	94%	X					X		X
78%	76%	33%	100%	X						X	
78%	72%	33%	94%	X						X	X
78%	85%	33%	100%	X							X
89%	89%	33%	83%		X						
89%	93%	67%	94%		X	X					
78%	83%	67%	100%		X	X	X				
78%	81%	67%	100%		X	X	X	X			
89%	87%	33%	89%		X	X	X	X	X	X	
89%	78%	33%	89%		X	X	X	X	X	X	
89%	78%	33%	94%		X	X	X	X	X	X	X
89%	83%	33%	100%		X	X	X	X	X	X	X
78%	76%	67%	100%		X	X	X	X		X	
78%	74%	67%	100%		X	X	X	X		X	X
78%	80%	67%	100%		X	X	X	X			X
89%	85%	33%	94%		X	X	X		X		
89%	78%	33%	89%		X	X	X		X	X	
89%	78%	33%	94%		X	X	X		X	X	X
89%	85%	33%	100%		X	X	X		X		X
78%	76%	67%	100%		X	X	X			X	
78%	74%	67%	100%		X	X	X			X	X
78%	80%	67%	100%		X	X	X				X
78%	87%	67%	94%		X	X		X			
89%	83%	33%	89%		X	X		X	X	X	
89%	81%	33%	89%		X	X		X	X	X	
89%	81%	33%	94%		X	X		X	X	X	X
89%	87%	33%	100%		X	X		X	X	X	X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	80%	67%	100%		X	X		X		X	
78%	78%	67%	100%		X	X		X		X	X
78%	85%	67%	100%		X	X		X			X
89%	87%	33%	89%		X	X			X		
89%	83%	33%	94%		X	X			X	X	
89%	83%	33%	100%		X	X			X	X	X
89%	87%	33%	100%		X	X			X		X
78%	80%	67%	100%		X	X				X	
78%	76%	67%	100%		X	X				X	X
78%	87%	67%	100%		X	X					X
78%	85%	67%	100%		X		X				
78%	85%	67%	100%		X		X	X			
100%	83%	33%	100%		X		X	X	X	X	
89%	81%	33%	94%		X		X	X	X	X	
89%	80%	33%	94%		X		X	X	X	X	X
89%	85%	33%	100%		X		X	X	X	X	X
78%	76%	67%	100%		X		X	X		X	
78%	76%	67%	100%		X		X	X		X	X
78%	85%	67%	100%		X		X	X			X
100%	83%	33%	100%		X		X		X		
89%	81%	33%	100%		X		X		X	X	
89%	81%	33%	100%		X		X		X	X	X
89%	85%	33%	100%		X		X		X		X
78%	78%	67%	94%		X		X			X	
78%	76%	67%	94%		X		X			X	X
78%	83%	67%	100%		X		X				X
89%	83%	67%	89%		X			X			
100%	78%	33%	78%		X			X	X	X	
89%	81%	33%	94%		X			X	X	X	
89%	85%	33%	100%		X			X	X	X	X
100%	83%	33%	100%		X			X	X	X	X
78%	83%	67%	100%		X			X		X	
78%	83%	67%	100%		X			X		X	X
78%	87%	67%	100%		X			X			X
100%	67%	67%	72%		X				X		
89%	83%	33%	94%		X				X	X	
89%	85%	33%	100%		X				X	X	X
100%	81%	33%	100%		X				X		X
89%	87%	67%	100%		X					X	
78%	80%	67%	100%		X					X	X
78%	85%	67%	100%		X						X
78%	76%	67%	89%			X					
78%	67%	67%	94%			X	X				
78%	67%	67%	89%			X	X	X			

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	76%	33%	89%			X	X	X	X	X	
89%	76%	33%	89%			X	X	X	X	X	
89%	76%	33%	94%			X	X	X	X	X	X
89%	76%	33%	94%			X	X	X	X	X	X
78%	63%	67%	78%			X	X	X		X	
78%	63%	67%	83%			X	X	X		X	X
78%	63%	67%	94%			X	X	X			X
89%	76%	33%	89%			X	X		X		
89%	76%	33%	89%			X	X		X	X	
89%	78%	33%	94%			X	X		X	X	X
89%	76%	33%	94%			X	X		X		X
78%	63%	67%	83%			X	X			X	
78%	61%	67%	89%			X	X			X	X
78%	67%	67%	94%			X	X				X
78%	67%	67%	83%			X		X			
89%	81%	33%	89%			X		X	X	X	
89%	76%	33%	89%			X		X	X	X	
89%	78%	33%	94%			X		X	X	X	X
89%	80%	33%	89%			X		X	X	X	X
78%	65%	67%	78%			X		X		X	
78%	63%	67%	94%			X		X		X	X
78%	69%	67%	94%			X		X			X
89%	78%	33%	89%			X			X		
89%	76%	33%	89%			X			X	X	
89%	78%	33%	94%			X			X	X	X
89%	81%	33%	94%			X			X		X
78%	65%	67%	72%			X				X	
78%	65%	67%	89%			X				X	X
78%	72%	67%	100%			X					X
78%	63%	67%	83%				X				
78%	61%	67%	89%				X	X			
100%	76%	33%	89%				X	X	X	X	
89%	74%	33%	94%				X	X	X	X	
89%	76%	33%	94%				X	X	X	X	X
89%	76%	33%	94%				X	X	X	X	X
78%	63%	67%	83%				X	X		X	
78%	61%	67%	83%				X	X		X	X
78%	61%	67%	89%				X	X			X
100%	74%	33%	94%				X		X		
89%	74%	33%	94%				X		X	X	
89%	76%	33%	94%				X		X	X	X
89%	78%	33%	94%				X		X		X
78%	61%	67%	78%				X			X	
78%	61%	67%	83%				X			X	X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	59%	67%	89%				X				X
67%	65%	33%	89%					X			
100%	69%	33%	72%					X	X	X	
89%	74%	33%	89%					X	X	X	
89%	76%	33%	94%					X	X	X	X
100%	76%	33%	94%					X	X	X	X
78%	61%	67%	78%					X		X	
78%	61%	67%	89%					X		X	X
78%	65%	33%	100%					X			X
100%	52%	67%	56%						X		
89%	74%	33%	89%						X	X	
89%	76%	33%	94%						X	X	X
100%	74%	33%	94%						X		X
78%	61%	67%	83%							X	
78%	61%	67%	83%							X	X
78%	76%	33%	100%								X

Table 3

Comprehensive List of Variables Used for Predicting Outbreak During Week—
High Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak one week in advance for high peak years.

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
56%	98%	0%	100%	X							
89%	96%	0%	94%	X	X						
67%	98%	0%	100%	X	X	X					
67%	93%	67%	100%	X	X	X	X				
78%	91%	67%	100%	X	X	X	X	X			
100%	85%	0%	94%	X	X	X	X	X	X	X	
89%	83%	0%	94%	X	X	X	X	X	X	X	
89%	83%	0%	100%	X	X	X	X	X	X	X	X
100%	83%	0%	100%	X	X	X	X	X	X	X	X
78%	87%	67%	100%	X	X	X	X	X		X	
78%	81%	67%	100%	X	X	X	X	X		X	X
78%	87%	67%	100%	X	X	X	X	X			X
100%	83%	0%	89%	X	X	X	X		X		
89%	81%	0%	94%	X	X	X	X		X	X	
89%	81%	0%	94%	X	X	X	X		X	X	X
100%	81%	0%	89%	X	X	X	X		X		X
67%	89%	67%	100%	X	X	X	X			X	
67%	85%	67%	100%	X	X	X	X			X	X
67%	89%	67%	100%	X	X	X	X				X
78%	94%	0%	100%	X	X	X		X			
100%	83%	0%	89%	X	X	X		X	X	X	
100%	85%	0%	94%	X	X	X		X	X	X	
100%	83%	0%	94%	X	X	X		X	X	X	X
100%	85%	0%	94%	X	X	X		X	X	X	X
78%	91%	67%	100%	X	X	X		X		X	
78%	87%	67%	100%	X	X	X		X		X	X
78%	91%	0%	100%	X	X	X		X			X
100%	81%	0%	83%	X	X	X			X		
100%	83%	0%	94%	X	X	X			X	X	
89%	81%	0%	94%	X	X	X			X	X	X
100%	83%	0%	89%	X	X	X			X		X
67%	94%	67%	100%	X	X	X				X	
67%	89%	67%	100%	X	X	X				X	X
78%	93%	0%	100%	X	X	X					X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	93%	33%	100%	X	X		X				
78%	93%	0%	100%	X	X		X	X			
100%	81%	0%	89%	X	X		X	X	X	X	
100%	80%	0%	94%	X	X		X	X	X	X	
100%	80%	0%	100%	X	X		X	X	X	X	X
100%	80%	0%	94%	X	X		X	X	X	X	X
78%	87%	67%	100%	X	X		X	X		X	
78%	78%	67%	100%	X	X		X	X		X	X
78%	85%	67%	100%	X	X		X	X			X
100%	80%	0%	89%	X	X		X		X		
100%	80%	0%	89%	X	X		X		X	X	
100%	80%	0%	94%	X	X		X		X	X	X
100%	80%	0%	89%	X	X		X		X		X
78%	89%	67%	100%	X	X		X			X	
78%	78%	67%	100%	X	X		X			X	X
78%	89%	67%	100%	X	X		X				X
89%	96%	0%	100%	X	X			X			
100%	81%	0%	83%	X	X			X	X	X	
100%	81%	0%	94%	X	X			X	X	X	
100%	80%	0%	100%	X	X			X	X	X	X
100%	83%	0%	94%	X	X			X	X	X	X
78%	93%	33%	100%	X	X			X		X	
78%	85%	67%	100%	X	X			X		X	X
78%	93%	0%	100%	X	X			X			X
100%	67%	0%	61%	X	X				X		
100%	80%	0%	89%	X	X				X	X	
100%	80%	0%	89%	X	X				X	X	X
100%	80%	0%	89%	X	X				X		X
78%	93%	33%	100%	X	X					X	
78%	89%	67%	100%	X	X					X	X
78%	91%	0%	100%	X	X						X
67%	91%	33%	89%	X		X					
67%	80%	33%	89%	X		X	X				
78%	80%	33%	89%	X		X	X	X			
100%	80%	0%	94%	X		X	X	X	X	X	
89%	80%	0%	94%	X		X	X	X	X	X	
89%	80%	0%	100%	X		X	X	X	X	X	X
100%	80%	0%	100%	X		X	X	X	X	X	X
67%	74%	67%	89%	X		X	X	X		X	
78%	67%	67%	83%	X		X	X	X		X	X
78%	74%	67%	94%	X		X	X	X			X
100%	80%	0%	89%	X		X	X		X		
89%	78%	0%	89%	X		X	X		X	X	
89%	80%	0%	89%	X		X	X		X	X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	80%	0%	89%	X		X	X		X		X
67%	74%	67%	83%	X		X	X			X	
67%	70%	67%	89%	X		X	X			X	X
67%	74%	67%	89%	X		X	X				X
78%	83%	0%	94%	X		X		X			
100%	81%	0%	94%	X		X		X	X	X	
89%	83%	0%	94%	X		X		X	X	X	
89%	80%	0%	94%	X		X		X	X	X	X
100%	81%	0%	94%	X		X		X	X	X	X
78%	76%	33%	89%	X		X		X		X	
78%	74%	67%	89%	X		X		X		X	X
78%	80%	33%	89%	X		X		X			X
100%	81%	33%	72%	X		X			X		
89%	81%	0%	89%	X		X			X	X	
89%	80%	0%	89%	X		X			X	X	X
100%	81%	0%	89%	X		X			X		X
67%	78%	33%	89%	X		X				X	
67%	76%	67%	94%	X		X				X	X
67%	80%	33%	100%	X		X					X
67%	85%	33%	89%	X			X				
78%	81%	33%	94%	X			X	X			
100%	74%	0%	89%	X			X	X	X	X	
100%	76%	0%	89%	X			X	X	X	X	
100%	78%	0%	94%	X			X	X	X	X	X
100%	78%	0%	94%	X			X	X	X	X	X
78%	70%	67%	89%	X			X	X		X	
78%	65%	67%	89%	X			X	X		X	X
78%	74%	67%	89%	X			X	X			X
100%	74%	0%	89%	X			X		X		
100%	76%	0%	89%	X			X		X	X	
100%	76%	0%	89%	X			X		X	X	X
100%	76%	0%	89%	X			X		X		X
67%	70%	67%	89%	X			X			X	
67%	65%	67%	89%	X			X			X	X
67%	78%	33%	89%	X			X				X
78%	94%	0%	94%	X				X			
100%	72%	0%	72%	X				X	X	X	
100%	72%	0%	89%	X				X	X	X	
100%	76%	0%	94%	X				X	X	X	X
100%	76%	0%	89%	X				X	X	X	X
78%	72%	33%	89%	X				X		X	
78%	70%	67%	89%	X				X		X	X
78%	83%	0%	100%	X				X			X
100%	61%	33%	50%	X					X		

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	78%	0%	89%	X					X	X	
100%	76%	0%	89%	X					X	X	X
100%	70%	0%	89%	X					X		X
67%	81%	33%	89%	X						X	
67%	74%	67%	89%	X						X	X
67%	85%	33%	94%	X							X
56%	94%	33%	94%		X						
67%	98%	33%	94%		X	X					
67%	89%	67%	94%		X	X	X				
78%	85%	67%	94%		X	X	X	X			
100%	83%	0%	94%		X	X	X	X	X	X	
89%	81%	0%	94%		X	X	X	X	X	X	
89%	81%	0%	100%		X	X	X	X	X	X	X
100%	81%	0%	100%		X	X	X	X	X	X	X
67%	85%	67%	94%		X	X	X	X		X	
78%	76%	67%	100%		X	X	X	X		X	X
78%	83%	67%	100%		X	X	X	X			X
100%	80%	0%	89%		X	X	X		X		
89%	80%	0%	89%		X	X	X		X	X	
89%	80%	0%	89%		X	X	X		X	X	X
100%	80%	0%	89%		X	X	X		X		X
67%	87%	67%	94%		X	X	X			X	
67%	80%	67%	100%		X	X	X			X	X
67%	85%	67%	100%		X	X	X				X
78%	94%	33%	94%		X	X		X			
100%	80%	0%	89%		X	X		X	X	X	
100%	83%	0%	94%		X	X		X	X	X	
100%	81%	0%	100%		X	X		X	X	X	X
100%	83%	0%	94%		X	X		X	X	X	X
78%	87%	67%	94%		X	X		X		X	
78%	83%	67%	94%		X	X		X		X	X
78%	87%	33%	100%		X	X		X			X
100%	72%	0%	67%		X	X			X		
100%	80%	0%	89%		X	X			X	X	
100%	80%	0%	89%		X	X			X	X	X
100%	81%	0%	89%		X	X			X		X
67%	89%	67%	94%		X	X				X	
67%	85%	67%	100%		X	X				X	X
67%	91%	33%	100%		X	X					X
67%	91%	67%	100%		X		X				
78%	87%	33%	100%		X		X	X			
100%	81%	0%	89%		X		X	X	X	X	
100%	80%	0%	94%		X		X	X	X	X	
100%	80%	0%	94%		X		X	X	X	X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	80%	0%	94%		X		X	X	X	X	X
78%	81%	67%	100%		X		X	X		X	
78%	78%	67%	100%		X		X	X		X	X
78%	81%	67%	100%		X		X	X			X
100%	76%	0%	83%		X		X		X		
100%	78%	0%	89%		X		X		X	X	
100%	80%	0%	94%		X		X		X	X	X
100%	80%	0%	89%		X		X		X		X
67%	83%	67%	100%		X		X			X	
67%	80%	67%	100%		X		X			X	X
67%	89%	67%	100%		X		X				X
78%	85%	33%	100%		X			X			
100%	76%	0%	72%		X			X	X	X	
100%	78%	0%	89%		X			X	X	X	
100%	80%	0%	94%		X			X	X	X	X
100%	81%	0%	89%		X			X	X	X	X
78%	85%	67%	94%		X			X		X	
78%	81%	67%	100%		X			X		X	X
78%	89%	33%	100%		X			X			X
100%	63%	33%	61%		X				X		
100%	78%	0%	89%		X				X	X	
100%	80%	0%	89%		X				X	X	X
100%	74%	0%	83%		X				X		X
67%	91%	67%	100%		X					X	
67%	87%	67%	100%		X					X	X
67%	91%	33%	100%		X						X
67%	81%	33%	83%			X					
67%	74%	67%	83%			X	X				
67%	74%	67%	83%			X	X	X			
100%	80%	0%	94%			X	X	X	X	X	
89%	76%	0%	94%			X	X	X	X	X	
89%	78%	0%	100%			X	X	X	X	X	X
100%	78%	0%	100%			X	X	X	X	X	X
67%	69%	67%	83%			X	X	X		X	
67%	63%	67%	89%			X	X	X		X	X
67%	67%	67%	89%			X	X	X			X
100%	78%	0%	89%			X	X		X		
89%	76%	0%	89%			X	X		X	X	
89%	78%	0%	89%			X	X		X	X	X
100%	78%	0%	89%			X	X		X		X
67%	69%	67%	83%			X	X			X	
67%	65%	67%	89%			X	X			X	X
67%	67%	67%	94%			X	X				X
67%	76%	33%	83%			X		X			

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	74%	0%	83%			X		X	X	X	
89%	80%	0%	94%			X		X	X	X	
89%	78%	0%	94%			X		X	X	X	X
100%	78%	0%	94%			X		X	X	X	X
67%	67%	67%	83%			X		X		X	
67%	67%	67%	83%			X		X		X	X
67%	72%	67%	89%			X		X			X
100%	67%	33%	56%			X			X		
89%	78%	0%	89%			X			X	X	
89%	76%	0%	89%			X			X	X	X
100%	78%	0%	83%			X			X		X
67%	74%	67%	83%			X				X	
67%	69%	67%	94%			X				X	X
67%	74%	67%	94%			X					X
67%	67%	67%	89%				X				
78%	63%	67%	94%				X	X			
100%	74%	0%	83%				X	X	X	X	
100%	76%	0%	89%				X	X	X	X	
100%	76%	0%	94%				X	X	X	X	X
100%	76%	0%	94%				X	X	X	X	X
67%	61%	67%	83%				X	X		X	
78%	61%	67%	89%				X	X		X	X
78%	61%	67%	89%				X	X			X
100%	70%	0%	83%				X		X		
100%	76%	0%	89%				X		X	X	
100%	76%	0%	89%				X		X	X	X
100%	74%	0%	89%				X		X		X
67%	63%	67%	89%				X			X	
67%	63%	67%	89%				X			X	X
67%	63%	67%	89%				X				X
67%	74%	0%	94%					X			
100%	69%	0%	67%					X	X	X	
100%	72%	0%	83%					X	X	X	
100%	76%	0%	94%					X	X	X	X
100%	72%	0%	83%					X	X	X	X
78%	63%	67%	83%					X		X	
78%	61%	67%	89%					X		X	X
78%	70%	33%	94%					X			X
100%	57%	33%	50%						X		
100%	74%	33%	78%						X	X	
100%	76%	0%	89%						X	X	X
100%	70%	0%	83%						X		X
67%	69%	67%	83%							X	
67%	63%	67%	89%							X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
67%	72%	67%	94%								X

Table 4

Weather Variables Used for Predicting Outbreak Two Weeks in Advance—
High Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak two weeks in advance for high peak years.

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
56%	98%	0%	94%	X							
89%	98%	0%	83%	X	X						
67%	100%	0%	94%	X	X	X					
67%	93%	0%	94%	X	X	X	X				
67%	93%	0%	94%	X	X	X	X	X			
78%	85%	0%	89%	X	X	X	X	X	X	X	
78%	87%	0%	89%	X	X	X	X	X	X	X	
78%	85%	33%	94%	X	X	X	X	X	X	X	X
78%	85%	0%	89%	X	X	X	X	X	X	X	X
78%	81%	33%	94%	X	X	X	X	X		X	
78%	76%	67%	94%	X	X	X	X	X		X	X
78%	85%	33%	94%	X	X	X	X	X			X
78%	89%	0%	89%	X	X	X	X		X		
78%	87%	0%	94%	X	X	X	X		X	X	
78%	83%	33%	94%	X	X	X	X		X	X	X
78%	87%	0%	89%	X	X	X	X		X		X
67%	87%	33%	89%	X	X	X	X			X	
78%	76%	67%	89%	X	X	X	X			X	X
78%	85%	0%	94%	X	X	X	X				X
67%	98%	0%	100%	X	X	X		X			
89%	87%	0%	89%	X	X	X		X	X	X	
78%	87%	0%	89%	X	X	X		X	X	X	
78%	87%	0%	89%	X	X	X		X	X	X	X
89%	83%	0%	89%	X	X	X		X	X	X	X
67%	93%	0%	94%	X	X	X		X		X	
78%	83%	33%	94%	X	X	X		X		X	X
67%	94%	0%	100%	X	X	X		X			X
100%	83%	0%	72%	X	X	X			X		
78%	91%	0%	89%	X	X	X			X	X	
78%	87%	0%	89%	X	X	X			X	X	X
89%	85%	0%	89%	X	X	X			X		X
67%	93%	0%	89%	X	X	X				X	
78%	85%	33%	89%	X	X	X				X	X
67%	93%	0%	94%	X	X	X					X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	91%	0%	94%	X	X		X				
78%	89%	0%	100%	X	X		X	X			
89%	80%	0%	89%	X	X		X	X	X	X	
89%	85%	0%	89%	X	X		X	X	X	X	
78%	83%	33%	89%	X	X		X	X	X	X	X
89%	85%	0%	89%	X	X		X	X	X	X	X
78%	85%	33%	100%	X	X		X	X		X	
78%	78%	67%	100%	X	X		X	X		X	X
78%	81%	0%	100%	X	X		X	X			X
89%	80%	0%	89%	X	X		X		X		
78%	85%	33%	89%	X	X		X		X	X	
78%	83%	33%	89%	X	X		X		X	X	X
89%	78%	33%	89%	X	X		X		X		X
78%	85%	67%	94%	X	X		X			X	
78%	78%	67%	94%	X	X		X			X	X
78%	85%	33%	94%	X	X		X				X
89%	94%	0%	94%	X	X			X			
100%	81%	0%	83%	X	X			X	X	X	
89%	81%	0%	89%	X	X			X	X	X	
89%	85%	0%	89%	X	X			X	X	X	X
89%	80%	0%	89%	X	X			X	X	X	X
78%	91%	0%	100%	X	X			X		X	
78%	85%	0%	100%	X	X			X		X	X
89%	89%	0%	100%	X	X			X			X
100%	67%	0%	61%	X	X				X		
89%	80%	0%	89%	X	X				X	X	
89%	80%	33%	89%	X	X				X	X	X
89%	76%	0%	83%	X	X				X		X
78%	91%	0%	94%	X	X					X	
78%	85%	33%	94%	X	X					X	X
78%	91%	0%	94%	X	X						X
67%	93%	0%	89%	X		X					
67%	74%	0%	89%	X		X	X				
67%	74%	0%	94%	X		X	X	X			
78%	83%	0%	89%	X		X	X	X	X	X	
78%	85%	0%	89%	X		X	X	X	X	X	
78%	85%	33%	94%	X		X	X	X	X	X	X
78%	83%	0%	89%	X		X	X	X	X	X	X
67%	74%	33%	94%	X		X	X	X		X	
78%	72%	67%	94%	X		X	X	X		X	X
78%	72%	33%	94%	X		X	X	X			X
78%	89%	0%	89%	X		X	X		X		
78%	89%	33%	94%	X		X	X		X	X	
78%	83%	33%	100%	X		X	X		X	X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	85%	33%	89%	X		X	X		X		X
67%	74%	67%	89%	X		X	X			X	
78%	72%	67%	89%	X		X	X			X	X
67%	74%	67%	89%	X		X	X				X
67%	91%	0%	94%	X		X		X			
89%	85%	0%	83%	X		X		X	X	X	
78%	85%	0%	89%	X		X		X	X	X	
78%	83%	0%	89%	X		X		X	X	X	X
78%	81%	0%	89%	X		X		X	X	X	X
67%	74%	33%	94%	X		X		X		X	
78%	72%	33%	94%	X		X		X		X	X
67%	76%	0%	94%	X		X		X			X
100%	76%	0%	72%	X		X			X		
78%	89%	0%	89%	X		X			X	X	
78%	85%	33%	89%	X		X			X	X	X
78%	85%	0%	89%	X		X			X		X
67%	74%	0%	89%	X		X				X	
67%	74%	67%	89%	X		X				X	X
67%	74%	0%	89%	X		X					X
78%	76%	0%	94%	X			X				
78%	80%	0%	94%	X			X	X			
89%	78%	0%	89%	X			X	X	X	X	
78%	83%	33%	89%	X			X	X	X	X	
78%	83%	33%	89%	X			X	X	X	X	X
89%	81%	33%	89%	X			X	X	X	X	X
78%	72%	67%	94%	X			X	X		X	
78%	69%	67%	94%	X			X	X		X	X
78%	72%	33%	94%	X			X	X			X
89%	70%	0%	83%	X			X		X		
78%	81%	33%	89%	X			X		X	X	
78%	83%	33%	89%	X			X		X	X	X
89%	78%	33%	89%	X			X		X		X
78%	74%	67%	89%	X			X			X	
78%	69%	67%	89%	X			X			X	X
78%	76%	33%	94%	X			X				X
78%	93%	0%	100%	X				X			
100%	76%	0%	83%	X				X	X	X	
89%	80%	0%	89%	X				X	X	X	
89%	81%	33%	89%	X				X	X	X	X
89%	78%	0%	89%	X				X	X	X	X
78%	80%	0%	94%	X				X		X	
78%	72%	67%	94%	X				X		X	X
78%	80%	0%	100%	X				X			X
100%	61%	33%	56%	X					X		

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	72%	0%	83%	X					X	X	
78%	78%	33%	89%	X					X	X	X
89%	65%	0%	83%	X					X		X
78%	76%	0%	89%	X						X	
78%	76%	33%	89%	X						X	X
78%	80%	0%	94%	X							X
56%	96%	0%	83%		X						
67%	100%	0%	89%		X	X					
67%	89%	33%	89%		X	X	X				
67%	81%	33%	94%		X	X	X	X			
78%	83%	0%	89%		X	X	X	X	X	X	
78%	85%	33%	89%		X	X	X	X	X	X	
78%	85%	33%	94%		X	X	X	X	X	X	X
78%	83%	33%	89%		X	X	X	X	X	X	X
67%	74%	67%	94%		X	X	X	X		X	
78%	72%	67%	94%		X	X	X	X		X	X
78%	76%	67%	94%		X	X	X	X			X
78%	83%	0%	89%		X	X	X		X		
78%	83%	33%	89%		X	X	X		X	X	
78%	81%	33%	94%		X	X	X		X	X	X
78%	83%	33%	89%		X	X	X		X		X
67%	78%	67%	89%		X	X	X			X	
78%	72%	67%	89%		X	X	X			X	X
67%	80%	67%	89%		X	X	X				X
67%	94%	33%	94%		X	X		X			
89%	83%	0%	83%		X	X		X	X	X	
78%	83%	0%	89%		X	X		X	X	X	
78%	83%	0%	89%		X	X		X	X	X	X
89%	81%	0%	89%		X	X		X	X	X	X
67%	83%	33%	94%		X	X		X		X	
78%	74%	67%	94%		X	X		X		X	X
67%	85%	33%	94%		X	X		X			X
100%	72%	0%	72%		X	X			X		
78%	83%	0%	89%		X	X			X	X	
78%	83%	33%	89%		X	X			X	X	X
89%	81%	0%	89%		X	X			X		X
67%	89%	33%	89%		X	X				X	
67%	78%	67%	89%		X	X				X	X
67%	89%	33%	94%		X	X					X
78%	87%	33%	100%		X		X				
78%	83%	33%	100%		X		X	X			
89%	81%	0%	89%		X		X	X	X	X	
89%	83%	33%	89%		X		X	X	X	X	
78%	83%	33%	89%		X		X	X	X	X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	83%	33%	89%		X		X	X	X	X	X
78%	74%	67%	100%		X		X	X		X	
78%	70%	67%	100%		X		X	X		X	X
78%	76%	67%	100%		X		X	X			X
89%	74%	0%	89%		X		X		X		
78%	83%	33%	89%		X		X		X	X	
78%	81%	33%	89%		X		X		X	X	X
89%	78%	33%	89%		X		X		X		X
78%	78%	67%	94%		X		X			X	
78%	72%	67%	100%		X		X			X	X
78%	80%	67%	100%		X		X				X
78%	83%	0%	100%		X			X			
100%	78%	0%	83%		X			X	X	X	
89%	81%	0%	89%		X			X	X	X	
89%	83%	33%	89%		X			X	X	X	X
89%	80%	0%	89%		X			X	X	X	X
78%	83%	33%	100%		X			X		X	
78%	76%	67%	100%		X			X		X	X
78%	83%	33%	100%		X			X			X
100%	63%	33%	61%		X				X		
89%	76%	0%	89%		X				X	X	
89%	80%	33%	89%		X				X	X	X
89%	72%	0%	83%		X				X		X
78%	89%	33%	94%		X					X	
78%	80%	67%	100%		X					X	X
78%	87%	33%	100%		X						X
67%	91%	33%	89%			X					
67%	74%	33%	89%			X	X				
67%	70%	33%	94%			X	X	X			
78%	81%	0%	89%			X	X	X	X	X	
78%	81%	33%	94%			X	X	X	X	X	
78%	81%	33%	94%			X	X	X	X	X	X
78%	81%	33%	89%			X	X	X	X	X	X
67%	70%	67%	94%			X	X	X		X	
78%	67%	67%	94%			X	X	X		X	X
67%	70%	67%	94%			X	X	X			X
78%	80%	0%	89%			X	X		X		
78%	81%	33%	94%			X	X		X	X	
78%	81%	33%	94%			X	X		X	X	X
78%	81%	33%	89%			X	X		X		X
67%	72%	67%	89%			X	X			X	
67%	69%	67%	89%			X	X			X	X
67%	70%	67%	89%			X	X				X
67%	87%	33%	94%			X		X			

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	81%	0%	83%			X		X	X	X	
78%	81%	0%	89%			X		X	X	X	
78%	81%	33%	89%			X		X	X	X	X
78%	80%	0%	89%			X		X	X	X	X
67%	72%	33%	94%			X		X		X	
67%	70%	67%	94%			X		X		X	X
67%	69%	33%	94%			X		X			X
100%	63%	33%	72%			X			X		
78%	80%	0%	89%			X			X	X	
78%	81%	33%	89%			X			X	X	X
78%	80%	0%	89%			X			X		X
67%	74%	33%	89%			X				X	
67%	72%	67%	89%			X				X	X
67%	74%	33%	89%			X					X
78%	69%	67%	94%				X				
78%	67%	67%	94%				X	X			
89%	80%	33%	89%				X	X	X	X	
78%	81%	33%	89%				X	X	X	X	
78%	81%	33%	89%				X	X	X	X	X
89%	81%	33%	89%				X	X	X	X	X
78%	65%	67%	94%				X	X		X	
78%	63%	67%	94%				X	X		X	X
78%	63%	67%	94%				X	X			X
89%	65%	33%	83%				X		X		
78%	81%	33%	89%				X		X	X	
78%	81%	33%	89%				X		X	X	X
89%	74%	33%	89%				X		X		X
78%	67%	67%	89%				X			X	
78%	65%	67%	89%				X			X	X
78%	65%	67%	89%				X				X
56%	80%	0%	94%					X			
100%	74%	33%	83%					X	X	X	
89%	80%	33%	89%					X	X	X	
89%	81%	33%	89%					X	X	X	X
89%	78%	33%	89%					X	X	X	X
78%	70%	67%	94%					X		X	
78%	63%	67%	94%					X		X	X
78%	65%	67%	94%					X			X
100%	54%	33%	44%						X		
89%	69%	33%	89%						X	X	
78%	76%	33%	89%						X	X	X
89%	63%	33%	83%						X		X
67%	72%	67%	89%							X	
78%	65%	67%	94%							X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	67%	67%	100%								X

Table 5

Weather Variables Used for Predicting Outbreak Three Weeks in Advance—
High Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak three weeks in advance for high peak years.

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
67%	96%	0%	83%	X							
78%	96%	0%	78%	X	X						
78%	93%	0%	89%	X	X	X					
78%	80%	0%	89%	X	X	X	X				
78%	81%	0%	94%	X	X	X	X	X			
89%	85%	33%	89%	X	X	X	X	X	X	X	
78%	83%	33%	89%	X	X	X	X	X	X	X	
78%	83%	33%	89%	X	X	X	X	X	X	X	X
78%	81%	33%	89%	X	X	X	X	X	X	X	X
78%	76%	33%	94%	X	X	X	X	X		X	
78%	76%	33%	94%	X	X	X	X	X		X	X
78%	81%	33%	89%	X	X	X	X	X			X
78%	85%	33%	89%	X	X	X	X		X		
78%	87%	33%	89%	X	X	X	X		X	X	
78%	87%	33%	89%	X	X	X	X		X	X	X
78%	89%	33%	89%	X	X	X	X		X		X
78%	78%	33%	89%	X	X	X	X			X	
78%	78%	33%	89%	X	X	X	X			X	X
78%	78%	0%	89%	X	X	X	X				X
78%	87%	0%	83%	X	X	X		X			
89%	83%	33%	89%	X	X	X		X	X	X	
78%	85%	33%	89%	X	X	X		X	X	X	
78%	81%	33%	89%	X	X	X		X	X	X	X
89%	81%	33%	89%	X	X	X		X	X	X	X
78%	81%	33%	94%	X	X	X		X		X	
78%	80%	33%	94%	X	X	X		X		X	X
78%	81%	0%	89%	X	X	X		X			X
100%	87%	33%	83%	X	X	X			X		
78%	85%	33%	89%	X	X	X			X	X	
78%	89%	33%	89%	X	X	X			X	X	X
89%	87%	33%	89%	X	X	X			X		X
78%	81%	0%	89%	X	X	X				X	
78%	78%	0%	89%	X	X	X				X	X
78%	81%	0%	89%	X	X	X					X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	81%	0%	89%	X	X		X				
78%	83%	0%	89%	X	X		X	X			
89%	80%	33%	89%	X	X		X	X	X	X	
89%	81%	33%	89%	X	X		X	X	X	X	
78%	81%	33%	89%	X	X		X	X	X	X	X
89%	80%	33%	89%	X	X		X	X	X	X	X
78%	78%	33%	94%	X	X		X	X		X	
78%	76%	33%	94%	X	X		X	X		X	X
78%	81%	0%	94%	X	X		X	X			X
89%	78%	33%	89%	X	X		X		X		
78%	85%	33%	89%	X	X		X		X	X	
78%	85%	33%	89%	X	X		X		X	X	X
89%	80%	33%	89%	X	X		X		X		X
78%	80%	0%	89%	X	X		X			X	
78%	78%	33%	94%	X	X		X			X	X
78%	80%	33%	89%	X	X		X				X
89%	87%	0%	83%	X	X			X			
100%	80%	33%	83%	X	X			X	X	X	
89%	83%	33%	89%	X	X			X	X	X	
89%	81%	33%	89%	X	X			X	X	X	X
89%	80%	33%	89%	X	X			X	X	X	X
78%	81%	0%	89%	X	X			X		X	
78%	81%	0%	94%	X	X			X		X	X
89%	83%	0%	83%	X	X			X			X
89%	65%	33%	83%	X	X				X		
89%	85%	33%	89%	X	X				X	X	
89%	81%	33%	89%	X	X				X	X	X
89%	76%	33%	89%	X	X				X		X
78%	81%	0%	89%	X	X					X	
78%	80%	0%	89%	X	X					X	X
78%	85%	0%	89%	X	X						X
67%	91%	0%	89%	X		X					
67%	80%	0%	89%	X		X	X				
78%	76%	33%	89%	X		X	X	X			
78%	81%	33%	89%	X		X	X	X	X	X	
78%	81%	33%	89%	X		X	X	X	X	X	
78%	83%	33%	89%	X		X	X	X	X	X	X
78%	78%	33%	89%	X		X	X	X	X	X	X
78%	74%	33%	94%	X		X	X	X		X	
78%	74%	33%	94%	X		X	X	X		X	X
78%	76%	33%	89%	X		X	X	X			X
78%	83%	33%	89%	X		X	X		X		
78%	87%	33%	89%	X		X	X		X	X	
78%	87%	33%	89%	X		X	X		X	X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
78%	87%	33%	89%	X		X	X		X		X
78%	76%	33%	89%	X		X	X			X	
78%	76%	33%	94%	X		X	X			X	X
78%	78%	33%	94%	X		X	X				X
67%	81%	0%	83%	X		X		X			
89%	83%	33%	89%	X		X		X	X	X	
78%	81%	33%	89%	X		X		X	X	X	
78%	78%	33%	89%	X		X		X	X	X	X
89%	81%	33%	89%	X		X		X	X	X	X
78%	78%	33%	94%	X		X		X		X	
78%	74%	33%	89%	X		X		X		X	X
78%	76%	0%	89%	X		X		X			X
100%	80%	33%	83%	X		X			X		
78%	85%	33%	89%	X		X			X	X	
78%	89%	33%	89%	X		X			X	X	X
78%	81%	33%	89%	X		X			X		X
78%	76%	33%	89%	X		X				X	
78%	78%	33%	94%	X		X				X	X
67%	80%	0%	89%	X		X					X
78%	81%	0%	83%	X			X				
78%	80%	0%	83%	X			X	X			
89%	80%	33%	89%	X			X	X	X	X	
78%	78%	33%	89%	X			X	X	X	X	
78%	80%	33%	89%	X			X	X	X	X	X
89%	80%	33%	89%	X			X	X	X	X	X
78%	76%	33%	94%	X			X	X		X	
78%	74%	33%	94%	X			X	X		X	X
78%	74%	33%	89%	X			X	X			X
89%	72%	33%	89%	X			X		X		
78%	83%	33%	89%	X			X		X	X	
78%	83%	33%	89%	X			X		X	X	X
89%	76%	33%	89%	X			X		X		X
78%	76%	33%	94%	X			X			X	
78%	78%	67%	94%	X			X			X	X
78%	78%	33%	94%	X			X				X
89%	85%	0%	83%	X				X			
100%	78%	33%	83%	X				X	X	X	
89%	80%	33%	89%	X				X	X	X	
89%	78%	33%	89%	X				X	X	X	X
89%	80%	33%	89%	X				X	X	X	X
78%	78%	33%	89%	X				X		X	
78%	76%	33%	94%	X				X		X	X
78%	78%	0%	83%	X				X			X
100%	59%	67%	61%	X					X		

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	78%	33%	89%	X					X	X	
78%	80%	33%	89%	X					X	X	X
89%	70%	33%	89%	X					X		X
78%	80%	0%	83%	X						X	
78%	78%	33%	94%	X						X	X
78%	81%	33%	89%	X							X
44%	91%	0%	89%		X						
67%	91%	0%	89%		X	X					
67%	80%	33%	94%		X	X	X				
78%	78%	33%	89%		X	X	X	X			
89%	81%	33%	89%		X	X	X	X	X	X	
78%	80%	33%	89%		X	X	X	X	X	X	
78%	81%	33%	89%		X	X	X	X	X	X	X
78%	80%	33%	89%		X	X	X	X	X	X	X
78%	70%	33%	94%		X	X	X	X		X	
78%	70%	33%	94%		X	X	X	X		X	X
78%	76%	33%	89%		X	X	X	X			X
78%	80%	33%	89%		X	X	X		X		
78%	80%	33%	89%		X	X	X		X	X	
78%	83%	33%	89%		X	X	X		X	X	X
78%	83%	33%	89%		X	X	X		X		X
78%	76%	33%	94%		X	X	X			X	
78%	74%	33%	94%		X	X	X			X	X
78%	74%	33%	94%		X	X	X				X
67%	81%	33%	89%		X	X		X			
89%	78%	33%	89%		X	X		X	X	X	
78%	81%	33%	89%		X	X		X	X	X	
78%	80%	33%	89%		X	X		X	X	X	X
89%	80%	33%	89%		X	X		X	X	X	X
78%	80%	33%	94%		X	X		X		X	
78%	70%	33%	94%		X	X		X		X	X
67%	80%	33%	89%		X	X		X			X
100%	76%	33%	83%		X	X			X		
78%	80%	33%	89%		X	X			X	X	
78%	80%	33%	89%		X	X			X	X	X
89%	80%	33%	89%		X	X			X		X
78%	80%	33%	94%		X	X				X	
78%	76%	33%	94%		X	X				X	X
67%	80%	33%	94%		X	X					X
78%	78%	33%	94%		X		X				
78%	76%	33%	89%		X		X	X			
89%	80%	33%	89%		X		X	X	X	X	
89%	80%	33%	89%		X		X	X	X	X	
78%	81%	33%	89%		X		X	X	X	X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	78%	33%	89%		X		X	X	X	X	X
78%	72%	33%	94%		X		X	X		X	
78%	69%	33%	94%		X		X	X		X	X
78%	70%	33%	89%		X		X	X			X
89%	72%	33%	89%		X		X		X		
78%	81%	33%	89%		X		X		X	X	
78%	83%	33%	89%		X		X		X	X	X
89%	78%	33%	89%		X		X		X		X
78%	76%	33%	94%		X		X			X	
78%	74%	67%	94%		X		X			X	X
78%	76%	67%	94%		X		X				X
78%	80%	0%	94%		X			X			
89%	78%	33%	83%		X			X	X	X	
89%	81%	33%	89%		X			X	X	X	
89%	80%	33%	89%		X			X	X	X	X
89%	80%	33%	89%		X			X	X	X	X
78%	74%	33%	94%		X			X		X	
78%	70%	33%	94%		X			X		X	X
78%	70%	0%	89%		X			X			X
89%	59%	67%	61%		X				X		
89%	78%	33%	89%		X				X	X	
89%	80%	33%	89%		X				X	X	X
89%	70%	33%	83%		X				X		X
78%	78%	33%	94%		X					X	
78%	76%	33%	94%		X					X	X
78%	74%	0%	94%		X						X
67%	89%	33%	94%			X					
67%	76%	33%	94%			X	X				
67%	76%	33%	89%			X	X	X			
78%	78%	33%	89%			X	X	X	X	X	
78%	80%	33%	89%			X	X	X	X	X	
78%	81%	33%	89%			X	X	X	X	X	X
78%	78%	33%	89%			X	X	X	X	X	X
78%	70%	33%	94%			X	X	X		X	
78%	70%	33%	94%			X	X	X		X	X
67%	72%	33%	89%			X	X	X			X
78%	80%	33%	89%			X	X		X		
78%	80%	33%	89%			X	X		X	X	
78%	83%	33%	89%			X	X		X	X	X
78%	80%	33%	89%			X	X		X		X
67%	76%	33%	94%			X	X			X	
78%	72%	33%	94%			X	X			X	X
67%	76%	33%	94%			X	X				X
67%	76%	33%	89%			X		X			

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
89%	80%	33%	89%			X		X	X	X	
78%	78%	33%	89%			X		X	X	X	
78%	78%	33%	89%			X		X	X	X	X
89%	80%	33%	89%			X		X	X	X	X
67%	78%	33%	89%			X		X		X	
78%	70%	33%	89%			X		X		X	X
67%	74%	33%	89%			X		X			X
100%	76%	67%	89%			X			X		
78%	80%	33%	89%			X			X	X	
78%	80%	33%	89%			X			X	X	X
78%	78%	33%	89%			X			X		X
67%	78%	33%	94%			X				X	
67%	74%	33%	94%			X				X	X
67%	78%	33%	94%			X					X
67%	78%	33%	94%				X				
78%	67%	33%	89%				X	X			
89%	78%	33%	89%				X	X	X	X	
78%	78%	33%	89%				X	X	X	X	
78%	78%	33%	89%				X	X	X	X	X
89%	78%	33%	89%				X	X	X	X	X
78%	69%	33%	94%				X	X		X	
78%	67%	33%	94%				X	X		X	X
78%	63%	67%	89%				X	X			X
89%	69%	33%	89%				X		X		
78%	80%	33%	89%				X		X	X	
78%	83%	33%	89%				X		X	X	X
89%	74%	33%	89%				X		X		X
78%	74%	33%	94%				X			X	
78%	72%	67%	94%				X			X	X
78%	72%	67%	94%				X				X
78%	72%	33%	94%					X			
89%	74%	33%	83%					X	X	X	
89%	78%	33%	89%					X	X	X	
89%	78%	33%	89%					X	X	X	X
89%	80%	33%	89%					X	X	X	X
78%	69%	33%	89%					X		X	
78%	67%	33%	89%					X		X	X
67%	69%	33%	94%					X			X
89%	54%	67%	39%						X		
89%	72%	33%	89%						X	X	
78%	76%	33%	89%						X	X	X
89%	63%	33%	83%						X		X
78%	74%	33%	94%							X	
78%	74%	67%	94%							X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
67%	74%	67%	94%								X

Table 6

Weather Variables Used for Predicting Outbreak During Week—
Low Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak during the week of the outbreak for low peak years.

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
57%	100%	0%	100%	X							
71%	95%	0%	100%	X	X						
100%	95%	0%	94%	X	X	X					
100%	86%	0%	100%	X	X	X	X				
100%	88%	0%	100%	X	X	X	X	X			
100%	90%	0%	89%	X	X	X	X	X	X	X	
100%	88%	0%	89%	X	X	X	X	X	X	X	
100%	88%	0%	100%	X	X	X	X	X	X	X	X
100%	90%	0%	94%	X	X	X	X	X	X	X	X
100%	83%	0%	100%	X	X	X	X	X		X	
100%	79%	0%	100%	X	X	X	X	X		X	X
100%	83%	0%	100%	X	X	X	X	X			X
100%	88%	0%	89%	X	X	X	X		X		
100%	86%	0%	94%	X	X	X	X		X	X	
100%	88%	0%	100%	X	X	X	X		X	X	X
100%	88%	0%	100%	X	X	X	X		X		X
100%	81%	0%	100%	X	X	X	X			X	
100%	79%	0%	100%	X	X	X	X			X	X
100%	83%	0%	100%	X	X	X	X				X
86%	98%	0%	94%	X	X	X		X			
100%	90%	0%	78%	X	X	X		X	X	X	
100%	88%	0%	89%	X	X	X		X	X	X	
100%	88%	0%	89%	X	X	X		X	X	X	X
100%	90%	0%	89%	X	X	X		X	X	X	X
100%	90%	0%	100%	X	X	X		X		X	
100%	83%	0%	100%	X	X	X		X		X	X
100%	90%	0%	100%	X	X	X		X			X
100%	88%	0%	78%	X	X	X			X		
100%	86%	0%	89%	X	X	X			X	X	
100%	88%	0%	94%	X	X	X			X	X	X
100%	90%	0%	89%	X	X	X			X		X
100%	88%	0%	100%	X	X	X				X	
100%	83%	0%	100%	X	X	X				X	X
100%	90%	0%	100%	X	X	X					X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	0%	100%	X	X		X				
100%	86%	0%	100%	X	X		X	X			
100%	90%	0%	89%	X	X		X	X	X	X	
100%	86%	0%	89%	X	X		X	X	X	X	
100%	88%	0%	100%	X	X		X	X	X	X	X
100%	88%	0%	94%	X	X		X	X	X	X	X
100%	81%	0%	100%	X	X		X	X		X	
86%	81%	0%	100%	X	X		X	X		X	X
100%	86%	0%	100%	X	X		X	X			X
100%	86%	0%	89%	X	X		X		X		
100%	86%	0%	94%	X	X		X		X	X	
100%	88%	0%	100%	X	X		X		X	X	X
100%	88%	0%	100%	X	X		X		X		X
100%	81%	0%	100%	X	X		X			X	
86%	79%	0%	100%	X	X		X			X	X
100%	83%	0%	100%	X	X		X				X
57%	95%	0%	94%	X	X			X			
100%	88%	0%	78%	X	X			X	X	X	
100%	86%	0%	89%	X	X			X	X	X	
100%	88%	0%	89%	X	X			X	X	X	X
100%	90%	0%	89%	X	X			X	X	X	X
100%	90%	0%	100%	X	X			X		X	
100%	83%	0%	100%	X	X			X		X	X
71%	90%	0%	100%	X	X			X			X
100%	83%	0%	72%	X	X				X		
100%	83%	0%	89%	X	X				X	X	
100%	88%	0%	94%	X	X				X	X	X
100%	88%	0%	83%	X	X				X		X
100%	88%	0%	100%	X	X					X	
100%	83%	0%	100%	X	X					X	X
86%	88%	0%	100%	X	X						X
71%	98%	0%	100%	X		X					
100%	83%	0%	100%	X		X	X				
100%	86%	0%	100%	X		X	X	X			
100%	88%	0%	83%	X		X	X	X	X	X	
100%	86%	0%	83%	X		X	X	X	X	X	
100%	86%	0%	94%	X		X	X	X	X	X	X
100%	88%	0%	89%	X		X	X	X	X	X	X
86%	79%	0%	100%	X		X	X	X		X	
86%	76%	0%	100%	X		X	X	X		X	X
86%	83%	0%	100%	X		X	X	X			X
100%	86%	0%	83%	X		X	X		X		
100%	86%	0%	89%	X		X	X		X	X	
100%	86%	0%	94%	X		X	X		X	X	X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	0%	94%	X		X	X		X		X
100%	76%	0%	100%	X		X	X			X	
86%	76%	0%	100%	X		X	X			X	X
86%	81%	0%	100%	X		X	X				X
86%	100%	0%	94%	X		X		X			
100%	90%	0%	72%	X		X		X	X	X	
100%	86%	0%	83%	X		X		X	X	X	
100%	86%	0%	83%	X		X		X	X	X	X
100%	88%	0%	89%	X		X		X	X	X	X
100%	88%	0%	100%	X		X		X		X	
86%	81%	0%	100%	X		X		X		X	X
100%	88%	0%	100%	X		X		X			X
100%	86%	0%	72%	X		X			X		
100%	86%	0%	83%	X		X			X	X	
100%	86%	0%	89%	X		X			X	X	X
100%	88%	0%	83%	X		X			X		X
100%	83%	0%	100%	X		X				X	
86%	81%	0%	100%	X		X				X	X
100%	86%	0%	100%	X		X					X
86%	81%	0%	100%	X			X				
71%	86%	0%	100%	X			X	X			
100%	88%	0%	89%	X			X	X	X	X	
100%	83%	0%	83%	X			X	X	X	X	
100%	86%	0%	94%	X			X	X	X	X	X
100%	86%	0%	89%	X			X	X	X	X	X
86%	79%	0%	100%	X			X	X		X	
86%	79%	33%	100%	X			X	X		X	X
86%	86%	0%	100%	X			X	X			X
100%	83%	0%	83%	X			X		X		
100%	83%	0%	89%	X			X		X	X	
100%	86%	0%	94%	X			X		X	X	X
100%	86%	0%	94%	X			X		X		X
86%	79%	0%	100%	X			X			X	
86%	76%	33%	100%	X			X			X	X
86%	83%	0%	100%	X			X				X
43%	95%	0%	89%	X				X			
100%	88%	33%	72%	X				X	X	X	
100%	83%	0%	83%	X				X	X	X	
100%	86%	0%	83%	X				X	X	X	X
100%	88%	0%	89%	X				X	X	X	X
100%	88%	0%	100%	X				X		X	
86%	83%	0%	100%	X				X		X	X
57%	86%	0%	100%	X				X			X
100%	81%	0%	67%	X					X		

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	81%	0%	83%	X					X	X	
100%	86%	0%	89%	X					X	X	X
100%	86%	0%	89%	X					X		X
100%	81%	0%	100%	X						X	
86%	81%	0%	100%	X						X	X
57%	86%	0%	100%	X							X
43%	90%	0%	78%		X						
86%	93%	0%	89%		X	X					
100%	81%	0%	100%		X	X	X				
100%	83%	0%	100%		X	X	X	X			
100%	86%	33%	83%		X	X	X	X	X	X	
100%	86%	33%	83%		X	X	X	X	X	X	
100%	86%	33%	94%		X	X	X	X	X	X	X
100%	86%	33%	83%		X	X	X	X	X	X	X
86%	76%	0%	100%		X	X	X	X		X	
86%	76%	0%	100%		X	X	X	X		X	X
86%	79%	0%	100%		X	X	X	X			X
100%	86%	33%	83%		X	X	X		X		
100%	86%	33%	89%		X	X	X		X	X	
100%	86%	33%	94%		X	X	X		X	X	X
100%	86%	33%	89%		X	X	X		X		X
86%	76%	0%	100%		X	X	X			X	
86%	74%	0%	100%		X	X	X			X	X
86%	76%	0%	100%		X	X	X				X
86%	95%	0%	89%		X	X		X			
100%	88%	33%	72%		X	X		X	X	X	
100%	86%	33%	83%		X	X		X	X	X	
100%	86%	33%	83%		X	X		X	X	X	X
100%	86%	33%	89%		X	X		X	X	X	X
100%	81%	0%	100%		X	X		X		X	
86%	79%	0%	100%		X	X		X		X	X
100%	88%	0%	100%		X	X		X			X
100%	83%	33%	72%		X	X			X		
100%	86%	33%	78%		X	X			X	X	
100%	86%	33%	89%		X	X			X	X	X
100%	86%	33%	89%		X	X			X		X
100%	76%	0%	94%		X	X				X	
86%	74%	0%	100%		X	X				X	X
100%	79%	0%	100%		X	X					X
86%	79%	0%	100%		X		X				
86%	81%	0%	100%		X		X	X			
100%	86%	33%	89%		X		X	X	X	X	
100%	86%	33%	83%		X		X	X	X	X	
100%	86%	33%	94%		X		X	X	X	X	X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	33%	89%		X		X	X	X	X	X
86%	74%	33%	100%		X		X	X		X	
86%	79%	33%	100%		X		X	X		X	X
86%	81%	33%	100%		X		X	X			X
100%	83%	33%	78%		X		X		X		
100%	86%	33%	89%		X		X		X	X	
100%	86%	33%	94%		X		X		X	X	X
100%	86%	33%	94%		X		X		X		X
86%	74%	33%	100%		X		X			X	
86%	76%	33%	100%		X		X			X	X
86%	76%	33%	100%		X		X				X
29%	90%	0%	94%		X			X			
100%	83%	67%	61%		X			X	X	X	
100%	86%	33%	83%		X			X	X	X	
100%	86%	33%	83%		X			X	X	X	X
100%	86%	33%	83%		X			X	X	X	X
100%	81%	0%	100%		X			X		X	
86%	79%	33%	100%		X			X		X	X
71%	88%	0%	100%		X			X			X
100%	79%	33%	56%		X				X		
100%	83%	33%	78%		X				X	X	
100%	86%	33%	89%		X				X	X	X
100%	83%	33%	83%		X				X		X
100%	71%	0%	94%		X					X	
86%	76%	33%	100%		X					X	X
71%	83%	0%	100%		X						X
57%	93%	0%	94%			X					
71%	71%	0%	94%			X	X				
71%	81%	0%	94%			X	X	X			
100%	83%	33%	83%			X	X	X	X	X	
100%	83%	33%	83%			X	X	X	X	X	
100%	83%	33%	94%			X	X	X	X	X	X
100%	86%	33%	83%			X	X	X	X	X	X
86%	74%	0%	94%			X	X	X		X	
86%	74%	0%	94%			X	X	X		X	X
86%	76%	0%	94%			X	X	X			X
100%	83%	33%	83%			X	X		X		
100%	83%	33%	89%			X	X		X	X	
100%	83%	33%	94%			X	X		X	X	X
100%	83%	33%	89%			X	X		X		X
71%	71%	0%	94%			X	X			X	
71%	69%	0%	94%			X	X			X	X
71%	74%	0%	94%			X	X				X
71%	93%	0%	89%			X		X			

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	83%	67%	67%			X		X	X	X	
100%	83%	33%	78%			X		X	X	X	
100%	83%	33%	83%			X		X	X	X	X
100%	86%	33%	83%			X		X	X	X	X
71%	81%	0%	94%			X		X		X	
86%	74%	0%	94%			X		X		X	X
86%	86%	0%	100%			X		X			X
100%	79%	67%	67%			X			X		
100%	83%	33%	72%			X			X	X	
100%	83%	33%	89%			X			X	X	X
100%	83%	33%	78%			X			X		X
71%	79%	0%	94%			X				X	
71%	71%	0%	94%			X				X	X
71%	79%	0%	94%			X					X
71%	74%	33%	94%				X				
86%	79%	33%	94%				X	X			
100%	81%	67%	83%				X	X	X	X	
100%	83%	33%	83%				X	X	X	X	
100%	83%	33%	94%				X	X	X	X	X
100%	83%	33%	89%				X	X	X	X	X
86%	74%	33%	94%				X	X		X	
86%	74%	33%	94%				X	X		X	X
86%	79%	33%	94%				X	X			X
100%	79%	33%	83%				X		X		
100%	83%	33%	89%				X		X	X	
100%	83%	33%	94%				X		X	X	X
100%	83%	33%	94%				X		X		X
86%	69%	33%	94%				X			X	
86%	69%	33%	94%				X			X	X
86%	74%	33%	94%				X				X
14%	93%	33%	83%					X			
100%	79%	67%	56%					X	X	X	
100%	83%	67%	78%					X	X	X	
100%	83%	33%	83%					X	X	X	X
100%	81%	33%	78%					X	X	X	X
86%	76%	0%	94%					X		X	
86%	79%	33%	94%					X		X	X
57%	86%	33%	100%					X			X
100%	74%	67%	50%						X		
100%	81%	33%	83%						X	X	
100%	83%	33%	89%						X	X	X
100%	79%	33%	67%						X		X
71%	69%	33%	94%							X	
86%	69%	33%	94%							X	X

Week 0				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
71%	83%	33%	100%								X

Table 7

Weather Variables Used for Predicting Outbreak One Week in Advance—
Low Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak one week in advance for low peak years.

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
57%	100%	0%	100%	X							
71%	90%	0%	78%	X	X						
100%	90%	0%	83%	X	X	X					
100%	93%	0%	94%	X	X	X	X				
100%	86%	0%	94%	X	X	X	X	X			
100%	83%	0%	83%	X	X	X	X	X	X	X	
100%	83%	0%	89%	X	X	X	X	X	X	X	
100%	83%	0%	89%	X	X	X	X	X	X	X	X
100%	83%	0%	89%	X	X	X	X	X	X	X	X
100%	79%	0%	94%	X	X	X	X	X		X	
100%	79%	0%	89%	X	X	X	X	X		X	X
100%	81%	0%	100%	X	X	X	X	X			X
100%	83%	0%	83%	X	X	X	X		X		
100%	83%	0%	89%	X	X	X	X		X	X	
100%	83%	0%	89%	X	X	X	X		X	X	X
100%	83%	0%	89%	X	X	X	X		X		X
100%	79%	0%	89%	X	X	X	X			X	
100%	79%	0%	89%	X	X	X	X			X	X
100%	86%	0%	94%	X	X	X	X				X
100%	90%	0%	78%	X	X	X		X			
100%	83%	0%	72%	X	X	X		X	X	X	
100%	86%	0%	83%	X	X	X		X	X	X	
100%	83%	0%	89%	X	X	X		X	X	X	X
100%	83%	0%	83%	X	X	X		X	X	X	X
100%	86%	0%	94%	X	X	X		X		X	
100%	83%	0%	94%	X	X	X		X		X	X
100%	90%	0%	100%	X	X	X		X			X
100%	83%	0%	72%	X	X	X			X		
100%	83%	0%	83%	X	X	X			X	X	
100%	83%	0%	89%	X	X	X			X	X	X
100%	83%	0%	83%	X	X	X			X		X
100%	90%	0%	94%	X	X	X				X	
100%	83%	0%	94%	X	X	X				X	X
100%	93%	0%	94%	X	X	X					X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	88%	0%	94%	X	X		X				
100%	86%	0%	100%	X	X		X	X			
100%	83%	0%	83%	X	X		X	X	X	X	
100%	83%	0%	89%	X	X		X	X	X	X	
100%	83%	0%	89%	X	X		X	X	X	X	X
100%	83%	0%	89%	X	X		X	X	X	X	X
100%	76%	0%	94%	X	X		X	X		X	
100%	76%	0%	100%	X	X		X	X		X	X
100%	79%	0%	100%	X	X		X	X			X
100%	83%	0%	83%	X	X		X		X		
100%	83%	0%	89%	X	X		X		X	X	
100%	83%	0%	89%	X	X		X		X	X	X
100%	83%	0%	89%	X	X		X		X		X
100%	76%	0%	94%	X	X		X			X	
100%	76%	0%	89%	X	X		X			X	X
100%	81%	0%	100%	X	X		X				X
86%	86%	0%	83%	X	X			X			
100%	83%	0%	56%	X	X			X	X	X	
100%	83%	0%	83%	X	X			X	X	X	
100%	83%	0%	89%	X	X			X	X	X	X
100%	83%	0%	83%	X	X			X	X	X	X
100%	86%	0%	94%	X	X			X		X	
100%	81%	0%	100%	X	X			X		X	X
100%	88%	0%	100%	X	X			X			X
100%	79%	0%	56%	X	X				X		
100%	83%	0%	83%	X	X				X	X	
100%	83%	0%	89%	X	X				X	X	X
100%	83%	0%	78%	X	X				X		X
100%	88%	0%	94%	X	X					X	
100%	83%	0%	94%	X	X					X	X
100%	90%	0%	100%	X	X						X
100%	93%	0%	94%	X		X					
100%	88%	0%	89%	X		X	X				
100%	86%	0%	89%	X		X	X	X			
100%	81%	0%	83%	X		X	X	X	X	X	
100%	81%	0%	89%	X		X	X	X	X	X	
100%	81%	0%	89%	X		X	X	X	X	X	X
100%	81%	0%	89%	X		X	X	X	X	X	X
100%	76%	0%	89%	X		X	X	X		X	
100%	79%	0%	89%	X		X	X	X		X	X
100%	83%	0%	94%	X		X	X	X			X
100%	81%	0%	83%	X		X	X		X		
100%	81%	0%	89%	X		X	X		X	X	
100%	81%	0%	94%	X		X	X		X	X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	81%	0%	89%	X		X	X		X		X
100%	74%	0%	89%	X		X	X			X	
100%	79%	0%	89%	X		X	X			X	X
86%	81%	0%	94%	X		X	X				X
100%	90%	0%	89%	X		X		X			
100%	81%	0%	72%	X		X		X	X	X	
100%	81%	0%	83%	X		X		X	X	X	
100%	81%	0%	89%	X		X		X	X	X	X
100%	81%	0%	83%	X		X		X	X	X	X
100%	79%	0%	89%	X		X		X		X	
100%	79%	0%	89%	X		X		X		X	X
100%	86%	0%	100%	X		X		X			X
100%	81%	33%	72%	X		X			X		
100%	81%	0%	83%	X		X			X	X	
100%	81%	0%	89%	X		X			X	X	X
100%	81%	0%	83%	X		X			X		X
100%	86%	0%	89%	X		X				X	
100%	83%	0%	89%	X		X				X	X
100%	90%	0%	94%	X		X					X
100%	86%	0%	94%	X			X				
100%	86%	0%	100%	X			X	X			
100%	81%	0%	83%	X			X	X	X	X	
100%	81%	0%	89%	X			X	X	X	X	
100%	81%	0%	89%	X			X	X	X	X	X
100%	81%	0%	89%	X			X	X	X	X	X
100%	74%	0%	89%	X			X	X		X	
100%	74%	0%	94%	X			X	X		X	X
100%	81%	0%	94%	X			X	X			X
100%	81%	0%	83%	X			X		X		
100%	81%	0%	89%	X			X		X	X	
100%	83%	0%	100%	X			X		X	X	X
100%	81%	0%	89%	X			X		X		X
100%	76%	0%	89%	X			X			X	
100%	71%	0%	94%	X			X			X	X
100%	79%	0%	94%	X			X				X
86%	95%	0%	100%	X				X			
100%	81%	0%	50%	X				X	X	X	
100%	81%	0%	83%	X				X	X	X	
100%	81%	0%	89%	X				X	X	X	X
100%	81%	0%	83%	X				X	X	X	X
100%	83%	0%	89%	X				X		X	
100%	81%	0%	94%	X				X		X	X
100%	88%	0%	100%	X				X			X
100%	71%	0%	50%	X					X		

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	81%	0%	83%	X					X	X	
100%	81%	0%	89%	X					X	X	X
100%	79%	0%	83%	X					X		X
100%	81%	0%	89%	X						X	
100%	81%	0%	94%	X						X	X
100%	90%	0%	100%	X							X
43%	90%	33%	72%		X						
100%	90%	33%	78%		X	X					
100%	81%	33%	94%		X	X	X				
100%	81%	33%	94%		X	X	X	X			
100%	83%	0%	83%		X	X	X	X	X	X	
100%	83%	0%	89%		X	X	X	X	X	X	
100%	83%	0%	89%		X	X	X	X	X	X	X
100%	83%	0%	89%		X	X	X	X	X	X	X
100%	76%	33%	89%		X	X	X	X		X	
100%	76%	0%	89%		X	X	X	X		X	X
100%	79%	0%	100%		X	X	X	X			X
100%	83%	0%	83%		X	X	X		X		
100%	83%	0%	89%		X	X	X		X	X	
100%	83%	0%	89%		X	X	X		X	X	X
100%	83%	0%	89%		X	X	X		X		X
100%	76%	33%	89%		X	X	X			X	
100%	76%	0%	89%		X	X	X			X	X
100%	79%	33%	89%		X	X	X				X
100%	88%	33%	78%		X	X		X			
100%	83%	0%	72%		X	X		X	X	X	
100%	83%	0%	83%		X	X		X	X	X	
100%	83%	0%	89%		X	X		X	X	X	X
100%	83%	0%	83%		X	X		X	X	X	X
100%	79%	33%	94%		X	X		X		X	
100%	79%	0%	94%		X	X		X		X	X
100%	81%	0%	100%		X	X		X			X
100%	83%	33%	67%		X	X			X		
100%	83%	0%	83%		X	X			X	X	
100%	83%	0%	89%		X	X			X	X	X
100%	83%	0%	83%		X	X			X		X
100%	81%	33%	94%		X	X				X	
100%	81%	0%	89%		X	X				X	X
100%	86%	33%	94%		X	X					X
100%	76%	33%	94%		X		X				
100%	71%	0%	100%		X		X	X			
100%	83%	0%	83%		X		X	X	X	X	
100%	83%	0%	89%		X		X	X	X	X	
100%	83%	0%	89%		X		X	X	X	X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	83%	0%	89%		X		X	X	X	X	X
100%	71%	0%	94%		X		X	X		X	
100%	71%	0%	94%		X		X	X		X	X
100%	74%	0%	100%		X		X	X			X
100%	83%	0%	83%		X		X		X		
100%	83%	0%	89%		X		X		X	X	
100%	83%	0%	89%		X		X		X	X	X
100%	83%	0%	89%		X		X		X		X
100%	71%	0%	89%		X		X			X	
100%	71%	0%	89%		X		X			X	X
100%	74%	0%	100%		X		X				X
100%	81%	0%	72%		X			X			
100%	81%	0%	50%		X			X	X	X	
100%	83%	0%	83%		X			X	X	X	
100%	83%	0%	89%		X			X	X	X	X
100%	83%	0%	78%		X			X	X	X	X
100%	71%	0%	94%		X			X		X	
100%	71%	0%	100%		X			X		X	X
100%	76%	0%	100%		X			X			X
100%	74%	33%	44%		X				X		
100%	83%	0%	83%		X				X	X	
100%	83%	0%	89%		X				X	X	X
100%	83%	0%	78%		X				X		X
100%	79%	0%	94%		X					X	
100%	74%	0%	94%		X					X	X
100%	86%	0%	100%		X						X
86%	88%	33%	89%			X					
86%	76%	33%	89%			X	X				
100%	79%	33%	89%			X	X	X			
100%	81%	0%	83%			X	X	X	X	X	
100%	81%	0%	89%			X	X	X	X	X	
100%	81%	0%	94%			X	X	X	X	X	X
100%	81%	0%	89%			X	X	X	X	X	X
100%	71%	0%	89%			X	X	X		X	
100%	76%	0%	89%			X	X	X		X	X
100%	76%	0%	94%			X	X	X			X
100%	81%	33%	83%			X	X		X		
100%	81%	0%	89%			X	X		X	X	
100%	81%	0%	94%			X	X		X	X	X
100%	81%	0%	89%			X	X		X		X
86%	74%	0%	89%			X	X			X	
86%	74%	0%	89%			X	X			X	X
86%	76%	0%	94%			X	X				X
100%	86%	0%	83%			X		X			

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	81%	0%	67%			X		X	X	X	
100%	81%	0%	83%			X		X	X	X	
100%	81%	0%	89%			X		X	X	X	X
100%	81%	0%	83%			X		X	X	X	X
100%	71%	0%	89%			X		X		X	
100%	76%	0%	89%			X		X		X	X
100%	79%	0%	94%			X		X			X
100%	79%	33%	72%			X			X		
100%	81%	33%	83%			X			X	X	
100%	81%	0%	89%			X			X	X	X
100%	81%	33%	83%			X			X		X
86%	74%	0%	89%			X				X	
86%	76%	0%	89%			X				X	X
86%	86%	0%	94%			X					X
71%	71%	0%	94%				X				
100%	71%	0%	94%				X	X			
100%	81%	0%	83%				X	X	X	X	
100%	81%	0%	89%				X	X	X	X	
100%	81%	0%	94%				X	X	X	X	X
100%	81%	0%	89%				X	X	X	X	X
100%	71%	0%	89%				X	X		X	
100%	71%	0%	94%				X	X		X	X
100%	74%	0%	94%				X	X			X
100%	81%	33%	83%				X		X		
100%	81%	0%	89%				X		X	X	
100%	81%	0%	94%				X		X	X	X
100%	81%	33%	89%				X		X		X
71%	69%	0%	89%				X			X	
71%	69%	0%	94%				X			X	X
71%	71%	0%	94%				X				X
86%	83%	0%	100%					X			
100%	79%	0%	50%					X	X	X	
100%	81%	0%	83%					X	X	X	
100%	81%	0%	89%					X	X	X	X
100%	81%	0%	78%					X	X	X	X
100%	74%	0%	89%					X		X	
100%	71%	0%	94%					X		X	X
100%	74%	0%	100%					X			X
100%	69%	33%	44%						X		
100%	79%	33%	83%						X	X	
100%	81%	0%	89%						X	X	X
100%	76%	67%	72%						X		X
71%	74%	0%	89%							X	
71%	71%	0%	94%							X	X

Week 1				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
71%	83%	0%	94%								X

Table 8

Weather Variables Used for Predicting Outbreak Two Weeks in Advance—
Low Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak two weeks in advance for low peak years.

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
71%	95%	33%	89%	X							
86%	93%	67%	78%	X	X						
86%	90%	67%	78%	X	X	X					
86%	88%	67%	89%	X	X	X	X				
100%	88%	33%	83%	X	X	X	X	X			
100%	88%	33%	89%	X	X	X	X	X	X	X	
100%	88%	33%	89%	X	X	X	X	X	X	X	
100%	88%	33%	89%	X	X	X	X	X	X	X	X
100%	88%	33%	89%	X	X	X	X	X	X	X	X
100%	83%	67%	89%	X	X	X	X	X		X	
100%	83%	67%	94%	X	X	X	X	X		X	X
100%	83%	33%	89%	X	X	X	X	X			X
100%	88%	33%	89%	X	X	X	X		X		
100%	88%	33%	89%	X	X	X	X		X	X	
100%	88%	33%	89%	X	X	X	X		X	X	X
100%	88%	33%	89%	X	X	X	X		X		X
100%	83%	67%	94%	X	X	X	X			X	
100%	83%	67%	94%	X	X	X	X			X	X
100%	83%	67%	94%	X	X	X	X				X
100%	86%	33%	78%	X	X	X		X			
100%	90%	33%	89%	X	X	X		X	X	X	
100%	88%	33%	89%	X	X	X		X	X	X	
100%	88%	33%	89%	X	X	X		X	X	X	X
100%	88%	33%	89%	X	X	X		X	X	X	X
100%	88%	33%	89%	X	X	X		X		X	
100%	83%	67%	89%	X	X	X		X		X	X
100%	88%	33%	83%	X	X	X		X			X
100%	88%	33%	89%	X	X	X			X		
100%	88%	33%	89%	X	X	X			X	X	
100%	88%	33%	89%	X	X	X			X	X	X
100%	88%	33%	89%	X	X	X			X		X
100%	88%	67%	89%	X	X	X				X	
100%	83%	67%	94%	X	X	X				X	X
86%	88%	67%	89%	X	X	X					X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	67%	94%	X	X		X				
100%	83%	33%	89%	X	X		X	X			
100%	88%	33%	89%	X	X		X	X	X	X	
100%	88%	33%	89%	X	X		X	X	X	X	
100%	88%	33%	89%	X	X		X	X	X	X	X
100%	88%	33%	89%	X	X		X	X	X	X	X
100%	86%	33%	89%	X	X		X	X		X	
100%	81%	33%	94%	X	X		X	X		X	X
100%	86%	33%	94%	X	X		X	X			X
100%	90%	33%	89%	X	X		X		X		
100%	88%	33%	89%	X	X		X		X	X	
100%	88%	33%	89%	X	X		X		X	X	X
100%	88%	33%	89%	X	X		X		X		X
100%	86%	67%	94%	X	X		X			X	
100%	81%	67%	94%	X	X		X			X	X
100%	86%	67%	100%	X	X		X				X
100%	86%	0%	78%	X	X			X			
100%	88%	33%	83%	X	X			X	X	X	
100%	88%	33%	89%	X	X			X	X	X	
100%	88%	33%	89%	X	X			X	X	X	X
100%	90%	33%	89%	X	X			X	X	X	X
100%	86%	33%	89%	X	X			X		X	
100%	86%	33%	89%	X	X			X		X	X
100%	88%	33%	89%	X	X			X			X
100%	81%	33%	67%	X	X				X		
100%	90%	33%	89%	X	X				X	X	
100%	88%	33%	89%	X	X				X	X	X
100%	90%	33%	89%	X	X				X		X
100%	88%	67%	89%	X	X					X	
100%	86%	67%	94%	X	X					X	X
100%	88%	67%	94%	X	X						X
86%	90%	67%	78%	X		X					
86%	81%	67%	94%	X		X	X				
100%	81%	33%	89%	X		X	X	X			
100%	86%	33%	89%	X		X	X	X	X	X	
100%	86%	33%	89%	X		X	X	X	X	X	
100%	83%	33%	89%	X		X	X	X	X	X	X
100%	86%	33%	89%	X		X	X	X	X	X	X
100%	79%	33%	94%	X		X	X	X		X	
100%	81%	33%	94%	X		X	X	X		X	X
100%	81%	33%	94%	X		X	X	X			X
100%	86%	33%	89%	X		X	X		X		
100%	86%	33%	89%	X		X	X		X	X	
100%	83%	33%	94%	X		X	X		X	X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	33%	89%	X		X	X		X		X
100%	81%	67%	94%	X		X	X			X	
100%	81%	67%	94%	X		X	X			X	X
86%	81%	67%	94%	X		X	X				X
100%	83%	0%	78%	X		X		X			
100%	88%	33%	89%	X		X		X	X	X	
100%	86%	33%	89%	X		X		X	X	X	
100%	86%	33%	89%	X		X		X	X	X	X
100%	86%	33%	89%	X		X		X	X	X	X
100%	81%	33%	89%	X		X		X		X	
100%	81%	33%	94%	X		X		X		X	X
100%	81%	33%	83%	X		X		X			X
100%	86%	33%	89%	X		X			X		
100%	86%	33%	89%	X		X			X	X	
100%	86%	33%	89%	X		X			X	X	X
100%	86%	33%	89%	X		X			X		X
86%	86%	67%	94%	X		X				X	
100%	81%	67%	94%	X		X				X	X
86%	83%	67%	89%	X		X					X
100%	81%	67%	94%	X			X				
100%	81%	0%	89%	X			X	X			
100%	86%	33%	89%	X			X	X	X	X	
100%	86%	33%	89%	X			X	X	X	X	
100%	86%	33%	94%	X			X	X	X	X	X
100%	86%	33%	89%	X			X	X	X	X	X
100%	79%	33%	94%	X			X	X		X	
100%	79%	33%	94%	X			X	X		X	X
100%	81%	33%	94%	X			X	X			X
100%	86%	33%	89%	X			X		X		
100%	86%	33%	94%	X			X		X	X	
100%	86%	33%	94%	X			X		X	X	X
100%	86%	33%	89%	X			X		X		X
100%	79%	67%	94%	X			X			X	
100%	81%	67%	94%	X			X			X	X
100%	81%	67%	94%	X			X				X
100%	83%	0%	83%	X				X			
100%	83%	33%	83%	X				X	X	X	
100%	86%	33%	89%	X				X	X	X	
100%	86%	33%	89%	X				X	X	X	X
100%	86%	33%	89%	X				X	X	X	X
100%	79%	0%	89%	X				X		X	
100%	81%	33%	94%	X				X		X	X
100%	81%	0%	83%	X				X			X
100%	74%	33%	67%	X					X		

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	33%	89%	X					X	X	
100%	86%	33%	89%	X					X	X	X
100%	83%	33%	89%	X					X		X
100%	81%	67%	94%	X						X	
100%	81%	67%	94%	X						X	X
100%	81%	67%	100%	X							X
57%	86%	67%	61%		X						
86%	93%	67%	72%		X	X					
86%	88%	67%	94%		X	X	X				
100%	88%	33%	89%		X	X	X	X			
100%	88%	33%	89%		X	X	X	X	X	X	
100%	88%	33%	89%		X	X	X	X	X	X	
100%	88%	33%	89%		X	X	X	X	X	X	X
100%	88%	33%	89%		X	X	X	X	X	X	X
100%	83%	33%	94%		X	X	X	X		X	
100%	81%	33%	94%		X	X	X	X		X	X
100%	83%	33%	94%		X	X	X	X			X
100%	88%	33%	89%		X	X	X		X		
100%	88%	33%	89%		X	X	X		X	X	
100%	88%	33%	94%		X	X	X		X	X	X
100%	86%	33%	89%		X	X	X		X		X
86%	81%	67%	94%		X	X	X			X	
86%	81%	67%	94%		X	X	X			X	X
86%	83%	67%	94%		X	X	X				X
100%	88%	33%	72%		X	X		X			
100%	90%	33%	78%		X	X		X	X	X	
100%	88%	33%	89%		X	X		X	X	X	
100%	88%	33%	89%		X	X		X	X	X	X
100%	90%	33%	89%		X	X		X	X	X	X
100%	88%	33%	89%		X	X		X		X	
100%	83%	33%	94%		X	X		X		X	X
100%	88%	33%	83%		X	X		X			X
100%	86%	33%	83%		X	X			X		
100%	90%	33%	89%		X	X			X	X	
100%	88%	33%	89%		X	X			X	X	X
100%	88%	33%	89%		X	X			X		X
86%	86%	67%	94%		X	X				X	
86%	83%	67%	94%		X	X				X	X
86%	88%	67%	89%		X	X					X
86%	86%	67%	100%		X		X				
100%	83%	33%	94%		X		X	X			
100%	90%	33%	89%		X		X	X	X	X	
100%	88%	33%	89%		X		X	X	X	X	
100%	88%	33%	94%		X		X	X	X	X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	88%	33%	89%		X		X	X	X	X	X
100%	83%	33%	94%		X		X	X		X	
100%	81%	33%	94%		X		X	X		X	X
100%	86%	33%	100%		X		X	X			X
100%	88%	33%	89%		X		X		X		
100%	88%	33%	89%		X		X		X	X	
100%	88%	33%	94%		X		X		X	X	X
100%	86%	33%	89%		X		X		X		X
100%	83%	67%	94%		X		X			X	
100%	81%	67%	94%		X		X			X	X
100%	86%	67%	100%		X		X				X
100%	83%	0%	72%		X			X			
100%	88%	33%	78%		X			X	X	X	
100%	90%	33%	89%		X			X	X	X	
100%	88%	33%	89%		X			X	X	X	X
100%	90%	33%	89%		X			X	X	X	X
100%	81%	33%	89%		X			X		X	
100%	86%	33%	94%		X			X		X	X
100%	86%	33%	89%		X			X			X
100%	79%	33%	61%		X				X		
100%	90%	33%	89%		X				X	X	
100%	88%	33%	89%		X				X	X	X
100%	88%	33%	89%		X				X		X
100%	83%	67%	100%		X					X	
100%	86%	67%	94%		X					X	X
86%	86%	67%	100%		X						X
57%	86%	33%	89%			X					
86%	81%	67%	94%			X	X				
100%	79%	33%	94%			X	X	X			
100%	86%	33%	89%			X	X	X	X	X	
100%	86%	33%	94%			X	X	X	X	X	
100%	83%	33%	94%			X	X	X	X	X	X
100%	86%	33%	89%			X	X	X	X	X	X
100%	76%	33%	94%			X	X	X		X	
100%	79%	33%	94%			X	X	X		X	X
100%	79%	33%	94%			X	X	X			X
100%	83%	33%	89%			X	X		X		
100%	86%	33%	94%			X	X		X	X	
100%	83%	33%	94%			X	X		X	X	X
100%	83%	33%	89%			X	X		X		X
86%	79%	67%	94%			X	X			X	
86%	79%	67%	94%			X	X			X	X
86%	81%	67%	94%			X	X				X
100%	83%	0%	72%			X		X			

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	88%	33%	89%			X		X	X	X	
100%	86%	33%	89%			X		X	X	X	
100%	86%	33%	89%			X		X	X	X	X
100%	86%	33%	89%			X		X	X	X	X
100%	76%	33%	94%			X		X		X	
100%	76%	33%	94%			X		X		X	X
100%	79%	33%	94%			X		X			X
100%	83%	33%	89%			X			X		
100%	86%	33%	89%			X			X	X	
100%	86%	33%	89%			X			X	X	X
100%	83%	33%	89%			X			X		X
86%	76%	67%	94%			X				X	
86%	79%	67%	94%			X				X	X
86%	81%	67%	94%			X					X
86%	81%	33%	94%				X				
100%	79%	0%	94%				X	X			
100%	86%	33%	89%				X	X	X	X	
100%	86%	33%	94%				X	X	X	X	
100%	86%	33%	94%				X	X	X	X	X
100%	86%	33%	89%				X	X	X	X	X
100%	79%	33%	94%				X	X		X	
100%	79%	33%	94%				X	X		X	X
100%	81%	33%	94%				X	X			X
100%	86%	33%	89%				X		X		
100%	86%	33%	94%				X		X	X	
100%	86%	33%	94%				X		X	X	X
100%	83%	33%	89%				X		X		X
100%	76%	67%	94%				X			X	
100%	79%	67%	94%				X			X	X
86%	81%	33%	94%				X				X
100%	76%	0%	83%					X			
100%	83%	33%	83%					X	X	X	
100%	86%	33%	89%					X	X	X	
100%	86%	33%	89%					X	X	X	X
100%	86%	33%	89%					X	X	X	X
100%	74%	0%	94%					X		X	
100%	79%	33%	94%					X		X	X
100%	81%	0%	100%					X			X
100%	69%	33%	61%						X		
100%	83%	33%	89%						X	X	
100%	86%	33%	89%						X	X	X
100%	83%	33%	89%						X		X
86%	76%	33%	94%							X	
100%	79%	67%	94%							X	X

Week 2				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
86%	81%	33%	100%								X

Table 9

Weather Variables Used for Predicting Outbreak Three Weeks in Advance—
Low Peak Years

A comprehensive list of the weather variable used in each of the 255 models considered here along with the sensitivity and specificity in both training and test for predicting the outbreak three weeks in advance for low peak years.

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
71%	93%	33%	94%	X							
86%	93%	33%	83%	X	X						
86%	93%	67%	78%	X	X	X					
86%	90%	67%	89%	X	X	X	X				
86%	88%	67%	83%	X	X	X	X	X			
100%	90%	33%	89%	X	X	X	X	X	X	X	
86%	88%	33%	89%	X	X	X	X	X	X	X	
86%	88%	33%	89%	X	X	X	X	X	X	X	X
86%	88%	33%	89%	X	X	X	X	X	X	X	X
86%	88%	67%	89%	X	X	X	X	X		X	
86%	88%	67%	89%	X	X	X	X	X		X	X
86%	88%	67%	89%	X	X	X	X	X			X
86%	93%	33%	89%	X	X	X	X		X		
86%	90%	33%	89%	X	X	X	X		X	X	
86%	88%	33%	94%	X	X	X	X		X	X	X
86%	88%	33%	89%	X	X	X	X		X		X
86%	88%	67%	89%	X	X	X	X			X	
86%	88%	67%	89%	X	X	X	X			X	X
86%	88%	67%	89%	X	X	X	X				X
100%	88%	33%	67%	X	X	X		X			
100%	93%	33%	83%	X	X	X		X	X	X	
100%	90%	33%	83%	X	X	X		X	X	X	
86%	88%	33%	89%	X	X	X		X	X	X	X
100%	90%	33%	89%	X	X	X		X	X	X	X
86%	88%	67%	78%	X	X	X		X		X	
86%	88%	67%	89%	X	X	X		X		X	X
86%	88%	67%	89%	X	X	X		X			X
100%	93%	33%	83%	X	X	X			X		
86%	93%	33%	83%	X	X	X			X	X	
86%	88%	33%	89%	X	X	X			X	X	X
86%	93%	33%	89%	X	X	X			X		X
86%	88%	67%	83%	X	X	X				X	
86%	88%	67%	89%	X	X	X				X	X
86%	90%	67%	89%	X	X	X					X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
86%	90%	67%	83%	X	X		X				
100%	88%	67%	89%	X	X		X	X			
100%	93%	33%	89%	X	X		X	X	X	X	
100%	90%	33%	89%	X	X		X	X	X	X	
86%	86%	33%	89%	X	X		X	X	X	X	X
100%	88%	33%	89%	X	X		X	X	X	X	X
86%	88%	67%	83%	X	X		X	X		X	
86%	88%	67%	89%	X	X		X	X		X	X
86%	88%	67%	83%	X	X		X	X			X
100%	93%	33%	89%	X	X		X		X		
86%	90%	33%	89%	X	X		X		X	X	
86%	86%	33%	89%	X	X		X		X	X	X
86%	88%	33%	89%	X	X		X		X		X
86%	88%	67%	89%	X	X		X			X	
86%	88%	67%	89%	X	X		X			X	X
86%	90%	67%	89%	X	X		X				X
100%	90%	33%	72%	X	X			X			
100%	93%	33%	83%	X	X			X	X	X	
100%	93%	33%	83%	X	X			X	X	X	
100%	88%	33%	89%	X	X			X	X	X	X
100%	93%	33%	89%	X	X			X	X	X	X
100%	88%	67%	89%	X	X			X		X	
86%	88%	67%	83%	X	X			X		X	X
100%	90%	33%	89%	X	X			X			X
100%	93%	33%	67%	X	X				X		
100%	93%	33%	89%	X	X				X	X	
86%	90%	33%	89%	X	X				X	X	X
100%	93%	33%	89%	X	X				X		X
86%	93%	67%	83%	X	X					X	
86%	88%	67%	89%	X	X					X	X
86%	90%	67%	89%	X	X						X
86%	90%	67%	78%	X		X					
86%	83%	67%	89%	X		X	X				
86%	83%	67%	89%	X		X	X	X			
100%	83%	33%	89%	X		X	X	X	X	X	
86%	86%	33%	94%	X		X	X	X	X	X	
86%	86%	33%	94%	X		X	X	X	X	X	X
86%	83%	33%	89%	X		X	X	X	X	X	X
86%	83%	67%	89%	X		X	X	X		X	
86%	83%	67%	89%	X		X	X	X		X	X
86%	83%	67%	89%	X		X	X	X			X
86%	90%	33%	94%	X		X	X		X		
86%	86%	33%	94%	X		X	X		X	X	
86%	86%	33%	94%	X		X	X		X	X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
86%	83%	33%	94%	X		X	X		X		X
86%	83%	67%	89%	X		X	X			X	
86%	83%	67%	89%	X		X	X			X	X
86%	86%	67%	89%	X		X	X				X
100%	79%	33%	72%	X		X		X			
100%	88%	33%	83%	X		X		X	X	X	
100%	88%	33%	83%	X		X		X	X	X	
86%	86%	33%	89%	X		X		X	X	X	X
100%	83%	33%	89%	X		X		X	X	X	X
86%	81%	67%	83%	X		X		X		X	
86%	83%	67%	89%	X		X		X		X	X
86%	81%	67%	89%	X		X		X			X
100%	86%	33%	83%	X		X			X		
86%	90%	33%	89%	X		X			X	X	
86%	86%	33%	94%	X		X			X	X	X
86%	88%	33%	94%	X		X			X		X
86%	83%	67%	83%	X		X				X	
86%	86%	67%	89%	X		X				X	X
86%	86%	67%	89%	X		X					X
86%	86%	67%	94%	X			X				
100%	81%	67%	89%	X			X	X			
100%	88%	33%	89%	X			X	X	X	X	
100%	86%	33%	89%	X			X	X	X	X	
86%	86%	33%	89%	X			X	X	X	X	X
100%	83%	33%	89%	X			X	X	X	X	X
86%	81%	67%	89%	X			X	X		X	
86%	81%	67%	89%	X			X	X		X	X
86%	81%	67%	94%	X			X	X			X
86%	88%	33%	89%	X			X		X		
86%	86%	33%	89%	X			X		X	X	
86%	86%	33%	89%	X			X		X	X	X
86%	83%	33%	83%	X			X		X		X
86%	83%	67%	89%	X			X			X	
86%	86%	67%	94%	X			X			X	X
86%	86%	67%	83%	X			X				X
100%	76%	33%	78%	X				X			
100%	88%	33%	83%	X				X	X	X	
100%	88%	33%	89%	X				X	X	X	
100%	83%	33%	89%	X				X	X	X	X
100%	88%	33%	89%	X				X	X	X	X
100%	81%	67%	89%	X				X		X	
86%	81%	67%	94%	X				X		X	X
100%	86%	33%	89%	X				X			X
100%	74%	33%	56%	X					X		

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
86%	90%	33%	89%	X					X	X	
86%	86%	33%	89%	X					X	X	X
86%	88%	33%	83%	X					X		X
86%	86%	67%	94%	X						X	
86%	86%	67%	89%	X						X	X
86%	88%	67%	89%	X							X
71%	90%	33%	67%		X						
86%	88%	67%	78%		X	X					
86%	88%	67%	89%		X	X	X				
86%	88%	67%	83%		X	X	X	X			
100%	90%	33%	83%		X	X	X	X	X	X	
86%	88%	33%	89%		X	X	X	X	X	X	
86%	88%	33%	89%		X	X	X	X	X	X	X
86%	88%	33%	89%		X	X	X	X	X	X	X
86%	88%	67%	89%		X	X	X	X		X	
86%	88%	67%	89%		X	X	X	X		X	X
86%	88%	67%	89%		X	X	X	X			X
86%	90%	33%	89%		X	X	X		X		
86%	88%	33%	94%		X	X	X		X	X	
86%	88%	33%	94%		X	X	X		X	X	X
86%	88%	33%	89%		X	X	X		X		X
86%	88%	67%	89%		X	X	X			X	
86%	88%	67%	89%		X	X	X			X	X
86%	88%	67%	89%		X	X	X				X
100%	86%	33%	72%		X	X		X			
100%	93%	33%	83%		X	X		X	X	X	
100%	90%	33%	83%		X	X		X	X	X	
86%	88%	33%	89%		X	X		X	X	X	X
100%	90%	33%	89%		X	X		X	X	X	X
86%	88%	67%	78%		X	X		X		X	
86%	88%	67%	89%		X	X		X		X	X
86%	88%	67%	89%		X	X		X			X
100%	93%	33%	83%		X	X			X		
86%	90%	33%	83%		X	X			X	X	
86%	88%	33%	89%		X	X			X	X	X
86%	93%	33%	89%		X	X			X		X
86%	88%	67%	83%		X	X				X	
86%	88%	67%	89%		X	X				X	X
86%	90%	67%	89%		X	X					X
86%	90%	67%	89%		X		X				
100%	88%	67%	89%		X		X	X			
100%	90%	33%	89%		X		X	X	X	X	
100%	88%	33%	89%		X		X	X	X	X	
86%	86%	33%	89%		X		X	X	X	X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	88%	33%	89%		X		X	X	X	X	X
86%	88%	67%	83%		X		X	X		X	
86%	88%	67%	89%		X		X	X		X	X
86%	88%	67%	83%		X		X	X			X
86%	93%	33%	89%		X		X		X		
86%	90%	33%	89%		X		X		X	X	
86%	88%	33%	89%		X		X		X	X	X
86%	88%	33%	89%		X		X		X		X
86%	88%	67%	94%		X		X			X	
86%	88%	67%	94%		X		X			X	X
86%	88%	67%	94%		X		X				X
100%	88%	33%	72%		X			X			
100%	90%	33%	72%		X			X	X	X	
100%	90%	33%	83%		X			X	X	X	
100%	88%	33%	89%		X			X	X	X	X
100%	93%	33%	89%		X			X	X	X	X
100%	88%	67%	89%		X			X		X	
86%	88%	67%	83%		X			X		X	X
100%	88%	33%	89%		X			X			X
100%	79%	33%	56%		X				X		
86%	93%	33%	89%		X				X	X	
86%	90%	33%	89%		X				X	X	X
86%	93%	33%	89%		X				X		X
86%	88%	67%	89%		X					X	
86%	88%	67%	94%		X					X	X
86%	90%	67%	83%		X						X
71%	83%	67%	78%			X					
86%	83%	67%	94%			X	X				
86%	81%	67%	83%			X	X	X			
100%	83%	33%	89%			X	X	X	X	X	
86%	86%	33%	94%			X	X	X	X	X	
86%	86%	33%	94%			X	X	X	X	X	X
86%	83%	33%	94%			X	X	X	X	X	X
86%	83%	67%	89%			X	X	X		X	
86%	83%	67%	89%			X	X	X		X	X
86%	83%	67%	89%			X	X	X			X
86%	83%	33%	94%			X	X		X		
86%	86%	33%	94%			X	X		X	X	
86%	86%	33%	94%			X	X		X	X	X
86%	83%	33%	94%			X	X		X		X
86%	83%	67%	94%			X	X			X	
86%	83%	67%	94%			X	X			X	X
86%	83%	67%	89%			X	X				X
100%	79%	33%	72%			X		X			

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
100%	86%	33%	83%			X		X	X	X	
100%	83%	33%	83%			X		X	X	X	
86%	83%	33%	94%			X		X	X	X	X
100%	83%	33%	89%			X		X	X	X	X
86%	81%	67%	83%			X		X		X	
86%	83%	67%	89%			X		X		X	X
86%	81%	67%	89%			X		X			X
100%	90%	33%	83%			X			X		
86%	90%	33%	89%			X			X	X	
86%	86%	33%	94%			X			X	X	X
86%	86%	33%	94%			X			X		X
86%	83%	67%	89%			X				X	
86%	83%	67%	94%			X				X	X
86%	83%	67%	94%			X					X
86%	83%	67%	94%				X				
86%	79%	67%	94%				X	X			
100%	86%	33%	89%				X	X	X	X	
100%	83%	33%	89%				X	X	X	X	
86%	83%	33%	89%				X	X	X	X	X
100%	83%	33%	89%				X	X	X	X	X
86%	81%	67%	89%				X	X		X	
86%	81%	67%	94%				X	X		X	X
86%	81%	67%	89%				X	X			X
86%	88%	33%	89%				X		X		
86%	86%	33%	89%				X		X	X	
86%	83%	33%	94%				X		X	X	X
86%	83%	33%	83%				X		X		X
86%	81%	67%	94%				X			X	
86%	83%	67%	94%				X			X	X
86%	86%	67%	89%				X				X
100%	71%	33%	72%					X			
100%	86%	33%	78%					X	X	X	
100%	88%	33%	89%					X	X	X	
100%	83%	33%	89%					X	X	X	X
100%	86%	33%	89%					X	X	X	X
86%	79%	67%	94%					X		X	
86%	81%	67%	89%					X		X	X
86%	81%	33%	94%					X			X
100%	62%	33%	44%						X		
86%	88%	33%	89%						X	X	
86%	83%	33%	89%						X	X	X
86%	88%	33%	83%						X		X
86%	83%	67%	94%							X	
86%	86%	67%	94%							X	X

Week 3				Variables Used In Model							
Train Sensitivity	Train Specificity	Test Sensitivity	Test Specificity	Pressure	Wind	Minimum Humidity	Average Temperature	Maximum Humidity	Precipitation	Maximum Temperature	Minimum Temperature
86%	86%	67%	94%								X

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